CONTRIBUTI DI RICERCA CRENOS

REGIONAL VARIATION IN APPRENTICESHIP AND PERMANENT EMPLOYMENT RATES: WHICH CAUSES?

Daniela Sonedda

WORKING PAPERS

2019/16

arkadia

CENTRO RICERCHE ECONOMICHE NORD SUD
(CRENOS)
UNIVERSITÀ DI CAGLIARI
UNIVERSITÀ DI SASSARI

CRENOS was set up in 1993 with the purpose of organising the joint research effort of economists from the two Sardinian universities (Cagliari and Sassari) investigating dualism at the international and regional level. CRENoS' primary aim is to improve knowledge on the economic gap between areas and to provide useful information for policy intervention. Particular attention is paid to the role of institutions, technological progress and diffusion of innovation in the process of convergence or divergence between economic areas. To carry out its research, CRENoS collaborates with research centres and universities at both national and international level. The centre is also active in the field of scientific dissemination, organizing conferences and workshops along with other activities such as seminars and summer schools.
CRENoS creates and manages several databases of various socio-economic variables on Italy and Sardinia. At the local level, CRENoS promotes and participates to projects impacting on the most relevant issues in the Sardinian economy, such as tourism, environment, transports and macroeconomic forecasts.

www.crenos.unica.it
crenos@unica.it

CRENoS – CAGLIARI
VIA SAN GIORGIO 12, I-09124 CAGLIARI, ITALIA
TEL. +39-070-6756397; FAX +39-070- 6756402

CRENoS - SASSARI
VIA MURONI 25, I-07100 SASSARI, ITALIA
TEL. +39-079-213511

Title: REGIONAL VARIATION IN APPRENTICESHIP AND PERMANENT EMPLOYMENT RATES: WHICH CAUSES?

ISBN: 978 88 68512 552

Prima Edizione: Dicembre 2019

Viale Bonaria 98 · 09125 Cagliari
Tel. 070/6848663 · info@arkadiaeditore.it
www.arkadiaeditore.it

Regional variation in apprenticeship and permanent employment rates: which causes?

Daniela Sonedda
University of Piemonte Orientale & CRENoS

Abstract

A fundamental observation of the 21st century is the substantial drop in permanent employment occupations. In this paper, I seek to understand the geographic variation in apprenticeship and the consequent permanent employment rates. I exploit a unique setting in Italy to verify whether regional disparities in general education and production systems play a key role in determining vocational apprenticeship rates and in determining how this labor contract creates job matches that persist over time. I find that when the quality of the regional education system is good, the medium-run gains in terms of permanent employment can be moderate. However, a small number of active firms in a region limits the quantity of job entries as apprentices.

Keywords: Human capital; local labour market; education system; production system.
Jel Classification: J24, J23, J21, I20, D2.

1 Introduction

What determines the geographic variation of apprenticeship and their conversion into permanent employment occupations? The ability to create not only jobs but good jobs is a prime policy issue as dictated by technological innovation and globalization processes. One expects that a commitment to invest in human capital can contribute to the creation of a good quality job and the consequent permanent employment position. If this is the case, apprenticeships have an advantage over the other labor contracts to lead to permanent employment. Why are not apprenticeships more widespread? The answer is because there exist influential factors that restrict their use. The question that I study, namely, the geographic variation of vocational apprenticeship and permanent employment rates as related to the regional education and production system, has received somewhat few attention. While there has been some interest in cross-country differences in apprenticeship rates, the within-country variation has been much less studied.

The aim of this paper is to investigate the role of the general education and production systems in determining the regional variation of vocational apprenticeship and the consequent permanent employment rates. I exploit Italian regional disparities in these systems and random assignment of individuals into regions at birth to shed light on this issue. Looking at geographic variations is important to fill some gaps in the literature. The presence of a legally enforceable commitment of the firms to training provision explains why firm-based vocational training schemes work in some countries but not in others (Dustmann and Schönberg 2012). However, this nationwide institutional setting is a necessary but not sufficient condition to influence the willingness of firms to provide training. For instance, on the basis of this argument only, it would be hard to justify the existence of differences within and across industries. These differences are analyzed by Dustmann and Schönberg (2009) who focus on the role of the degree of unionization. The argument that unions serve as commitment and as wage floor device is convincing. Nevertheless, further explanations are still missing. Otherwise, in countries like Switzerland and Germany where the apprenticeship labor contract works, regional differences are only due to differences in the degree of unionization (or in the degree of the enforceable commitment of the firms to training provision).

This paper contributes to the literature by presenting new empirical evidence that points to the importance of two influencing factors: the general education and production systems. Regional variations in these systems contribute to explain not only regional differences in the apprenticeship rate but also the extent to which apprenticeships serve as a stepping stone into permanent employment. To the best of my knowledge, this is the first paper that tackles this empirical issue.

I use a very rich administrative dataset, by the Italian Ministry of Labor and Social Policies, *CICO* (the so-called *Comunicazioni Obbligatorie*). I exploit a unique setting in Italy to analyze the role of the general education and production systems in determining the regional variation of vocational apprenticeship and the consequent permanent employment rates. Since 2008 apprenticeships in Italy are considered permanent labor contracts. However there are two important differences between apprenticeships and standard open-ended contract. Apprenticeships are committed to provide, for a certain period, on-the-job training and general education outside the firms. At the end of this training period the firm could withdraw from the contract with a notice without paying firing costs. In absence of this notice the firm converts automatically the contract into a standard permanent labor contract. The length of the training period mainly ranges between six months and 3 years while standard open-ended contracts have a maximum of six months of probationary

period. A reform introduced in 2012 by law no.92 enforced the usage of the apprenticeship labor contract as the main port of entry into permanent employment. On the top of these two facts, Italy is characterized by a further dualism within a dual labor market[1]: the North-South divide which is possibly related to regional disparities that interact with the functioning of the labor market.

I assume that the data generating process of the permanent employment rate is related to the legal rule that in Italy a job entry as apprentice is only available, albeit not mandatory, up to 29 years and 364 days of age. This yields to a discontinuity in the permanent employment rate around the cutoff of 30 years of age. This discontinuity in the permanent employment rate can depend on the apprenticeship labor contract only. There is no reason to observe such data generating process of permanent employment in case of transitions from either unemployment or from a temporary labor contract. On the top of that, I expect that the introduction of law no. 92/2012 has exogenously changed this data generating process. In fact, the law enforced a mentoring scheme to strengthen the vocational training component of the job. This rule was complemented by a future punishment to the firm that avoided to maintain on a permanent basis at least 30% of those hired as apprentices three years before. Hence, the reform reinforced the commitment of the firm to employ permanently the apprentices and discouraged the production oriented usage of the contract.

This unique setting allows me to design a difference in discontinuity regression model. That is, I can compare individuals who reached the threshold age after the introduction of the reform to similar untreated individuals born in contiguous cohorts who reached the cutoff age before the reform. Hence, the labor market reform, creates a source of randomized variation at the threshold age. Since this variation is randomized, it is independent of any observable factor that can be added as a covariate in the regression model, including the indicator of the location of work. This paper adds to the literature the analysis of the geographical variation of apprenticeship and the consequent permanent employment rates as related to regional differences in the education and production systems. On the one hand, these differences help explaining that the number of active firms in a region limits the quantity of job entries as apprentices. On the other hand, the quality of the education system affects the capacity of the apprenticeship labor contract to create jobs that persists over time. This analysis differs from the few existing studies using data at regional level in four crucial aspects (see for instance Brunello and De Paola 2008, Muehlemann and Wolter 2008). First, exploiting a randomized variation, this paper overcomes one of the major problem that has to be faced when analyzing regional differences in labor market outcomes: the region of work is not exogenous. In my research design, the heterogeneity across regions of the estimated difference in discontinuity effects on apprenticeship and permanent employment rates is entirely driven by the exogenous assignment of individuals into regions at birth. This generated a randomized source of geographic variation. On the top of that, the ignorability assumption clearly holds in my empirical analysis because individuals cannot control the features of the regional distribution of the average quality of the education system and firm landscape. Second, the main outcome is the individual's permanent employment probability and how it is related to the apprenticeship probability rather than the training decision of the firm. Third, I analyze the role of the quality of the regional education and production systems in determining the size of these difference in discontinuity impacts at the baseline and in the medium-run. For instance, it could

[1] According to the original definition of Doeringer and Piore (1971), labor markets are dual in nature if they are segregated into primary and secondary spheres.

be the case that in the medium-run it is not the number of firms or the number of employees per squared kilometer that matter *per sé*. If there are complementarities between former education and the on-the-job human capital investment, a qualitative, rather than a quantitative, measure of general education better contributes to determine the number of *potential* apprentices with long-term employment perspectives . This qualitative measure(s) corresponds to the percentage of individuals who scored the maximum level in the Programme for International Student Assessment (PISA) tests in math and reading performance. By the same token, the limited number of *active* firms in a region[2] could serve as a barrier to the quantity of successful apprenticeship labor contracts. In fact, for both employer and employees, the apprenticeship contract implies a costly investment whose future return is uncertain. It is, therefore, likely that only firms with medium-long terms production opportunities invest on it. Fourth, last but not least, any of these papers estimates the dynamic effects on permanent employment of the initial human capital investment.

I find that the capacity of the apprenticeship labor contract to serve as a stepping stone into permanent employment is limited when the quality of the education system is low and the number of active firms is small. Different results emerge when instead the quality of the education system is high. In such a case, the medium-run gains in terms of permanent employment are moderate. This is possibly revealing the existence of complementarities between former education and further human capital accumulation.

Hence, my contribution is to show that geographic variations in the education system coupled with difference production opportunities across regions can explain some of the observed facts of a North-South divide in Italy in permanent employment rates. In particular, it can explain why in some regions the quantity of job entries as apprentices is limited. Moreover, the existence of complementarities between former education and on-the-job human capital investment rationalizes the finding that regions with high quality of upper secondary education have higher permanent employment gains from the vocational apprenticeship labor contract.

The rest of the paper is organised as follows. Section 2 outlines the related literature. Section 3 describes the institutional framework and the geographic variation of those who have a higher permanent employment probability. Section 4 illustrates the data and Section 5 discusses the empirical model. Results are reported in section 6. Finally, section 7 concludes.

2 Related literature

The article is related to at least three strands of the literature.

First, the effect of dualism on labor markets has been widely analyzed, see for instance Dolado (2017). From every angle this issue is looked at, in a dual labor market employers are more reluctant to hire workers on a permanent basis. This literature focuses on the role of the employment protection legislation and reaches no clear consensus on which kind of labor contract can be used as the main port of entry into stable, high quality, employment. On the one hand, it is generally assumed that temporary contracts do not bear the firing costs which have to be paid to terminate permanent contracts. By decreasing firing costs, temporary jobs could, theoretically, be useful to young inexperienced workers to raise their job experience easing their transition towards permanent employment. After

[2]Of course, it is likely that the limited number of firms and the limited number of productive firms are correlated.

a period of screening, the firm could convert these contracts, letting them be stepping stones into permanent employment (Holmlund and Storrie 2002, Booth, Francesconi and Frank 2002, Heinrich, Mueser and Troske 2005, Ichino, Mealli and Nannicini 2008). However, as suggested by Cahuc, Charlot and Malherbet (2016), in all countries, open-ended occupations comprise probationary periods and temporary works cannot be terminated before their ending date. As a result, firms profitably screen temporary workers only if the duration of the probationary period is shorter than that of fixed term contracts. The authors consider a job search and matching model where the use of temporary contracts hinges on the heterogeneity of expected production opportunities. Short-term (even very short ones) contracts can emerge in equilibrium because they are used for production opportunities with short expected durations. Workers could, therefore, end up moving from one temporary contract to another letting these contracts be dead-end jobs (Blanchard and Landier 2002, Cahuc and Postel-Vinay 2002, Boeri and Garibaldi 2007). Moreover, as the expected duration of fixed term contracts gets shorter, firms are less likely to invest in workers' training because the return of this investment in human capital is low, if positive. Besides, fixed-terms workers are more likely to lose their incentives to exert more effort to accumulate better productive capabilities. As a result, the successfulness of temporary labor contracts to help employers to screen workers' ability and employees to sort in better jobs could be limited.

Second, I complement the literature on the determinants of firm sponsored training. I present new empirical evidence on the factors that could make an investment in human capital be a device to optimize the screening-sorting processes that lead to permanent employment. To this extent, the apprenticeship labor contract can have an advantage over the other labor contracts. In Italy since 2008 apprenticeship contracts are considered permanent labor contracts. Vocational apprenticeship training allows individuals to accumulate human capital which translates into ex-post higher productivity. The informational content of the contract is crucial here. In fact, informational asymmetries convert general into specific training since the current employer has an informational advantage on his employees' productivity relative to other firms (Acemoglu and Pischke 1998, Acemoglu and Pischke 1999). Both firms (in terms of monopsony rents) and individuals (in terms of higher future wages and higher probability of permanent employment) benefit of the higher worker's productivity. Firms and workers share also the cost of this human capital investment. Firms are required, to train on-the-job the apprentice and during time of work, to let him/her attend external courses provided by local authorities or accredited training institutes sponsored by the regions. Firms are partly compensated for the training costs by a tax rebate. From the workers' perspective the apprenticeship labor contract is costly because it requires costly effort and it implies a lower initial wage. To some extent, the lower initial wage eliminates the wage rigidity which prevents an offsetting transfer from workers to firms in exchange for being insured against job losses (Lazear 1990). In fact, there are some analogies with a contract that fix a performance related pay component of (future) earnings. The costs of the vocational training and the general education provided by the contract and the lower initial wage are compensated by a permanent labor contract and higher earnings in the future. The rationale is here similar to Macho-Stadler, Perez-Castrillo and Porteiro (2014) who argue that long-term contracts allow the better provision of incentives because firms can credibly transfer payments from earlier to later periods in the life of the workers. The higher the worker effort is, the higher the probability of a long-lasting employment relationship, the higher future earnings will be.

However, there might be further explanations on the successfulness of the apprenticeship labor contract over and above the informational content. In absence of these further

mechanisms it would be difficult to explain differences across countries. In fact, information asymmetries and skill specificity are not likely to vary greatly across countries while institutional attributes do. An important contribution in this direction is provided by Dustmann and Schönberg (2012) who relate the successfulness of apprenticeships to the commitment to training provision guaranteed by the countries' institutional framework. While the authors focus on a mechanism which clearly explains why apprenticeship performs better in a country rather than another, it does not completely address the issue of why there might be differences across regions, sectors and occupations *within* a country. A potential explanation of the existence of within and across industries differences relies on Dustmann and Schönberg (2009) who account for such differences in terms of the degree of unionization. In fact, unions set a wage floor, which is another influencing factor of the firm decision to provide training. From the employees' perspective, unionized firms offer a long-term wage contract. In the future, at least the union wage has to be paid. From the employer's point of view, the unions' wage floor determines wage compression. As long as the equilibrium wage structure is more compressed than the productivity differentials, the firm makes greater profits from more skilled workers. Consequently, if the training costs are not too large, it is profitable for the employer to invest in the employee's human capital (Acemoglu and Pischke 1998, Acemoglu and Pischke 1999). Dustmann and Schönberg (2009) provide empirical evidence that apprenticeship training is higher in unionized firms in Germany. However, geographic variations in apprenticeship rates are hardly explained by regional differences in the degree of unionization.

Third, very few papers present empirical evidence on the firm decision to provide training using data at regional level. Brunello and De Paola (2008) study the relationship between local labor market density and firm sponsored training. The local labour market density is measured by the number of employees per squared kilometer in a province. The authors show that, theoretically, the effect of economic density on the firm decision to train cannot be signed. On the one hand, a higher density of the local labor market increases productivity and consequently encourages firms to invest more in training. On the other hand, a higher density of the local labor market reduces the rents of the firms and consequently lowers the incentive to train. They use data on more than 1000 Italian manufacturing firms, drawn from the Survey of Italian Manufacturing by Mediocredito Centrale, to present estimates on such relationship. They find that the local agglomeration pattern has a negative and statistically different from zero impact on the willingness of the firms to invest in the employees' human capital. Muehlemann and Wolter (2008) use a representative firm level data set to estimate whether the local industry structure and education system affects the decision of the firm to hire apprentices in Switzerland. The local industry structure is proxied by the number of competing firms situated in the same geographical area. In the attempt to avoid endogeneity issues related to the geographical location of the firm, the authors define the geographical area in terms of travel distances rather than political borders. The local education system is measured in three different ways: by the local number of young people of school-leaving age; by the local share of pupils of foreign nationality and by the local share of young people completing compulsory education that opted for grammar schools in 1995. They find that while the number of competing firms situated in the same geographical area affects negatively the probability of apprenticeship training, the number of young people of school-leaving age in the area has instead a positive impact on it.

Although there is an emerging line of inquiry studying the relationship between local labor markets and geography, there is limited, if any, work done on the geographic variation in vocational apprenticeship and permanent employment rates and their relationship with

the regional education and production systems. My understanding of the observed differences in permanent occupations across regions and their implications is an understudied area of research in economic geography. In this paper, I seek to unpack these geographic variations and how this may inform on how a labor contract committed to a costly human capital investment, serves as a stepping stone into permanent employment. Specifically, I exploit a unique setting to study these relationships looking at the geographic heterogeneity in Italy of the impact of the labor market reform (law no. 92/2012) at the threshold of 30 years of age, above which job entries as vocational apprentices are not possible.

3 Institutional framework and geographic variations in permanent employment probability

Since 2001 Italian regions have exclusive power to legislate over vocational training and they are responsible for planning the integration between the vocational training and the school system. For this reason when law no 30/2003 and legislative decree no. 276/2003 introduced new normative requirements for the apprenticeship labor contract, regional governments had to issue regional regulations. The timing of the implementation of the 2003 reform was therefore different across regions and across sectors because of different timing in contract renewals. Cappellari, Dell'Aringa and Leonardi (2012) exploit this variability across regions and sectors to show that this reform had an overall productivity enhancing effect. The 2003 reform also introduced the vocational apprenticeship labor contract to which I give my attention. Here, instead, I neglect the role of the traditional apprenticeship contract (apprenticeship for vocational qualifications and diplomas, upper secondary education diplomas and high technical specialization certificates), that can be assimilated to a vocational and education training program alternative to a more academic track. This is because the age limit for this contract is below the age range considered in my analysis. In what follows, vocational apprenticeship is a open-ended (since 2008) labor contract committed to an initial human capital investment whose age limit to be signed is 29 years and 364 days. Despite the open-ended nature of the contract, the firm can withdraw from it when the training period expires. If the employer does not, the apprenticeship labor contract is automatically converted into a standard permanent contract. Legislative decree no. 167/2011, established a common regulation across all regions. For this reason, I do not exploit the geographic variations generated by law no 30/2003. Rather I take advantage of the fact that in this common rule framework, law no. 92/2012, known as *Fornero Reform*, changed further the vocational apprenticeship labor contract. In fact, law no. 92/2012 implemented one of the major reform of the Italian labor market. The main changes concerned the contract of salaried employment, social safety nets and the dismissal regulations. In dealing with reforming the type and number of contract salaried, the law explicitly stated that apprenticeship labor contract was meant to be the main port of entry to permanent employment for young people. The law also fixed the minimum length of the training period to six months and the maximum length to three years (before it was six years), although there could be some exceptions. This implies that individuals aged more than 30 can work as apprentices but they cannot entry into a new job position as apprentices. The law enforced a mentoring scheme fixing a ratio between apprentices and qualified workers in the same job occupation. The law introduced a future punishment on the firms which did not accomplish with the open ended nature of the contract. In fact, these firms could not hire more than one apprentice three years after the job entry of the apprentices if less than 30% (50% since 2016) of them were not still

employed by the firm. Individual dismissals and motivated lay-offs are not included in the calculation of this percentage. Finally, the law increased the social security contributions burdened on temporary contracts while keeping fixed the tax rebate on apprenticeship contracts. All these three measures contribute to create a randomized source of variation that takes the form of a difference in discontinuity around the threshold age of 30. Since the institutional framework is common across all Italian regions, where could geographic variations come from? In what follows, I will focus on the average quality of the regional general education system and on the average number of active firms (and some of their characteristics) in a region as influencing factors in the creation of a permanent job position through the apprenticeship labor contract. These regional determinants play a role over and above differences in the quality of regional general education courses which were not affected by the labor market reform. Individuals can control their decision to migrate to another region when accepting a new job. Nevertheless, they cannot control the position in the corresponding regional distribution of the average quality of the general education system and on the average number of active firms in the region where they work. This argument could suffice to identify causal effects. Nevertheless, there is even a more strong argument that explains why the identified effects are causal and where the geographical variations come from. Distance from where one lives seems to be a very strong and negative predictor of job acceptance (Combes and Duranton 2006, Dal Bó, Finan and Rossi 2013, Manning and Petrongolo 2017). This is because of the existence of high commuting costs or idiosyncratic preferences for location. Other reasons geographical proximity may be an important factor of the creation of permanent occupations are the firm's informational cost of identifying the *good* worker and the individuals' informational cost of identifying the *good* firm. These informational costs are larger across regions than within them. As a result, geographic variation of good workers (and firms) might be observed as long as higher production opportunities and productivity advantages of agglomeration economies exist (Serafinelli forthcoming, Greenstone, Hornbeck and Moretti 2010, Combes, Duranton, Gobillon, Puga and Roux 2012, Gathmann, Helm and Schönberg forthcoming). I provide suggestive evidence of this geographic variation. I define potentially good workers similarly to Serafinelli (forthcoming) who identifies potentially high-productivity firms as those that pay a relatively high firm-specific wage premium. Here, good workers are expressed in terms of higher permanent employment advantages. Good workers are those who have a relatively high individual-specific probability of permanent employment. The estimated firm effects characterize firm production opportunities and are also helpful to underline the observed geographic variation in permanent job creation and its relationship with the regional education and production systems. This definition is consistent with recent models of frictional labor markets (e.g., Cahuc et al. (2016)), in which permanent employment occupations are created by firms with higher expected production opportunities.

For the working sample in the period from January 2010 to December 2014, I specify a linear probability model of permanent employment, as follows:

$$y_{ijt} = \theta_i + \psi_j + \phi_t + rw_{ijt} + r_i + s_{ijt} + b_1 X_{it} + u_{ijt} \tag{1}$$

where the dependent variable, the permanent employment probability of worker i who was born in region r and work in region rw in sector s for firm j in year t[3], is expressed as a function of individual heterogeneity, firm heterogeneity, and measured time-varying characteristics.[4]

[3]Time fixed effects are captured by both month and year dummies.

[4]I include as covariates a job (not individual) specific measure of the log of the first month real earnings

The presence of labor mobility in matched worker-firm dataset enables the identification of worker and firm effects. I define good workers as those whose estimated individual fixed effects fall within the top third of all estimated individual effects. In the on-line Appendix I display the distributions of these workers and firms fixed effects. Figure (1) reports the geographic variations across regions of work of employees and firms fixed effects for the sub-sample of good workers defined as above. The North-South divide that stems from this geographic variations is clear.[5]

[Figure 1 about here]

One could argue that this picture illustrates how individuals and firms sort into the region where they work or operate. If this was the case, the individual migration process could not be independent of the reform. However, as preliminary analysis, for each region of birth, the on-line Appendix will display the estimated difference in discontinuity effects on apprenticeship rates and (permanent) employment rates. These effects are not statistically different from those estimated on the basis of the individual region of work rather than birth. Consistently, there is not any difference in discontinuity in the migration process.[6] Hence, the randomized source of geographic variations that I am exploiting is the random assignment of individuals into the region where they were born. Unless we are ready to assume that the skill distribution of individuals at birth is different across regions, there might be some regional characteristics that improve (or worsen) the permanent employment prospects of individuals treated by the labor market reform at the age threshold.

4 Data

Data of the working sample are taken from a very rich administrative dataset by the Ministry of Labour and Social Policies, *CICO* (the so-called *Comunicazioni Obbligatorie*). In a given year, for each cohort of birth, the dataset gathers all individuals who are born on the 1st, the 9th, the 10th and the 11th of each month.

It includes, since 2009, the relevant dates (day, month, year) and detailed information of all job contracts, activated, transformed and dismissed, for dependent and independent (individuals with VAT number) workers for all sectors including the Agricultural sector and the Public Administration. The type of labour contract, the region of work and an anonymous identifier for both the firm and the worker and the type of benefit associated

and a bunch of dummies measuring whether, in a given month and year, the worker's educational level is higher than the 25th percentile of the education distribution conditional on age; if the worker's educational level is higher than the 75th percentile of the education distribution conditional on age; if the worker's past-experience is higher than the 75th percentile of the past-experience distribution conditional on age; if the worker's number of monthly multiple job spells is higher than the 25th percentile of the corresponding distribution conditional on age; if the job episode is associated to a number of monthly job separations higher than the 25th percentile of the corresponding distribution conditional on age and region of birth; if the job episode is associated to a number of monthly net flows (hirings minus separations) higher than the 25th percentile of the corresponding distribution conditional on age and region of birth; if the job episode benefited of a labor costs reduction higher than the 25th percentile of the corresponding distribution conditional on age, and if the job episode benefited of social insurance benefits higher than the 25th percentile of the corresponding distribution conditional on age.

[5] In the on-line Appendix I displays the geographical variations across regions of birth of these fixed effects. The North-South divide is even more pronounced.

[6] All these results are available from request from the author.

to the contract, if granted, are recorded in the dataset. Moreover, for each worker, I have information on the gender, the year of birth, the region of birth, citizenship and education.

The working sample is centered in a ±30 months interval around June 2012 when law no. 92 was issued. This implies that those treated (untreated) by the reform are those who (didn't) reach the threshold age of 30 between July 2012 to December 2014 (January 2010 to June 2012) ending up with two and half affected and unaffected cohorts. Since there is not precise information on the date of birth of the individual, to minimize measurement error in the definition of age, the latter is measured at the 31st December of the previous year. That is to say, for example, that in 2012 an individual is aged 29 with certainty if she is born in 1982 and she is turning to 30 in an unknown month during that year.

Using the information on the region of work, the database is merged with Bureau Van Dijk (AIDA) data. Unfortunately, the firm identification code in CICO data is anonymous. Hence the two datasets can be merged using only information on either the region of work or the region of birth. I consider the former to keep in my sample also foreign workers. AIDA contains comprehensive information on all Italian companies required to file their accounts, approximately 1 million companies. I consider those with a non-missing value on revenues amounting to 919, 456 (2010), 939, 488 (2011), 937, 170 (2012), 940, 106 (2013) and 947, 449 (2014) firms. However, I complement the analysis using other regional enterprises economic indicators provided by the Italian Statistical Office (ISTAT): the number of all active firms in a region; the regional firms' turnover rate; the share of high-tech firms over all regional firms; and the share of employees in high-tech occupation over all regional workers. I consider also several regional human capital indicators provided by ISTAT: the regional percentage of those who scored the maximum (minimum) level in the PISA test in math and reading performance; the regional share of upper secondary students who repeat the schooling year; the average number of enrolles per class and the average number of enrolles per school in upper secondary education; the regional dropout rate at upper secondary education. This allows me to provide a comprehensive view of the role of the education and production system that is not relegated to a specific measure.

I restrict the age interval of ±1 years around the age threshold considering only those who started either a job spell or a self-employment activity[7] in a given year. The working sample, therefore, amounts to 2, 132, 899 observations gathering 168,542 individuals and 152,225 firms.

5 Empirical model

I start by assuming that the data generating process of the apprenticeship rate is based on the legal rule that, in Italy, job entry as apprentice is only available, albeit not mandatory, up to 29 years and 364 days of age. This yields to a deterministic process of the apprenticeship rate on one side of the cutoff of 30 years. As a consequence, the data generating process of permanent employment rate exhibits a discontinuity around this age threshold that can only be related to the apprenticeship rate. On the top of that, I expect that the introduction of law no. 92/2012 has exogenously changed this data generating process. This setting allows me to design a difference in discontinuity regression model. In the on-line Appendix, I present suggestive evidence on the main assumption of the design. Potential outcome is continuous in age because individuals and firms have imprecise control on the age at which the apprenticeship labor contract is signed (if it is signed). The validity of

[7] I have information on self-employment activities by merging CICO data with two datasets recording self-employment and independent jobs episodes in the professional orders.

this hypothesis has two main implications. First, observable covariates are irrelevant and unnecessary for identification. This is because the randomized variation allows to compare individuals who have similar observable and unobservable characteristics. Second, as long as the variation is randomized the conditional independence assumption with respect to the individual's region of work (and birth) holds. This design, then, creates a suitable framework to estimate the geographic variation in permanent job creation and its relationship with the regional education and production systems. The regression model 2 is, therefore, augmented to grant for heterogeneous effects which rely on the characteristics of the regional systems. This is a restricted model specification of a difference in regression discontinuity design. These model restrictions are imposed by the data since I have information only on the worker's year of birth:

$$y_{i,t} = \alpha_{1v} + \alpha_1 k_{it} + \gamma_1 d_{it} k_{it} + \gamma_0 d_{it} + v_i + \sum_{v=2}^{v=4} \beta_{1v} d_{it} v_i + \sum_{v=2}^{v=4} \alpha_{1v} k_{it} v_i + \sum_{v=2}^{v=4} \gamma_{1v} d_{it} k_{it} v_i + \epsilon_{i,t} \quad (2)$$

where $y_{i,t}$ is the outcome for individual i at time (year, month) t; k_{it} is an indicator function which takes the value of 1 if the individual, given her age and year of birth, is treated by law no. 92/2012 and d_{it} is an indicator function that takes the value of 1 if the person is aged less than 30 years and v_i are the dummies for the quartiles of the distribution of a regional indicator for either the education or the production system.

That is to say, for instance, that the dummy for the second quartile takes the value of 1 if a certain region sits in the second quartile of the distribution of this regional indicator. The ignorability assumption clearly holds here since individuals cannot control the features of the distribution of regional indicators that determine the relative position of the region where they work.

In what follows, I will consider as outcome y: the employment probability, the permanent employment probability and the apprenticeship probability.

The interpretation of the Intention To Treat, ITT, parameter, γ_1, simplifies to measuring to what extent, around the age threshold, the outcome of interest changes for individuals treated by law no. 92/2012 compared to similar individuals born in contiguous cohorts, who reached the threshold age before the introduction of the law. However, equation 2 implies that the difference in discontinuity impact may differ across the regional position (quartiles) in the distribution of the regional indicator of either the education or production system. Hence being born at the right time to be treated by a reform, that reinforces the open-ended nature of apprenticeships, in the right place, where the regional context favors the successfulness of the contract, matters. Similar untreated individuals who didn't grow up in such favorable environment have lower permanent employment probabilities.

To strengthen this interpretation I extend the analysis to a dynamic setting. The following regression model takes into account the persistency in outcome generated by the exogenous shock of the reform at the age threshold[8] and allows to retrieve the dynamic ITT parameter:

[8]That is to say that I expect that if job entry as apprentice serves as stepping stone into permanent employment, in the months following the baseline, the current permanent employment position depends also on the permanent employment position at the baseline which in turn is related to the impact of the labor market reform around the age cutoff.

$$
\begin{aligned}
y_{i,t} = \alpha_{1v} + \alpha_1 k_{it} + \gamma_1 d_{it} k_{it} + \gamma_0 d_{it} + v_i + \beta_{1v} d_{it} v_i + \alpha_{1v} k_{it} v_{it} + \gamma_{1v} d_{it} k_{it} v_{it} \\
+ \phi_\tau \sum_{\tau=1}^{\tilde{\tau}} (\alpha_1 k_{i,t-\tau} + \gamma_\tau^{TOT} d_{i,t-\tau} k_{i,t-\tau} + \gamma_0 d_{i,t-\tau} + \sum_{v=2}^{v=4} \alpha_{1v} k_{i,t-\tau} v_i \\
+ \sum_{v=2}^{v=4} \gamma_{\tau v}^{TOT} d_{i,t-\tau} k_{i,t-\tau} v_i + \sum_{v=2}^{v=4} \gamma_{0v} d_{i,t-\tau} v_i) + \epsilon_{i,t}
\end{aligned} \tag{3}
$$

where for each quartile of the regional indicator $\gamma_{\tau v}^{ITT} = \gamma_{\tau v}^{TOT} + \sum_{h=1}^{\tau v} \gamma_{\tau - hv}^{TOT} \phi_h$ estimates the dynamic ITT effects.

The model is estimated in the range of ± 1 year of age around the cutoff. For this reason, it is not possible to include in equation 2 the forcing variable age (parameterized as deviation from 30) that is perfectly collinear with the indicator function d_{it}. In fact, the discrete character of the age variable forces the regression model to require a functional form assumption. I can show that this functional form assumption is supported by the data in the smallest age range.[9] Nevertheless, if potential outcome is continuous in age and the parametric model is not too restrictive, the appealing characteristics of the regression discontinuity design are preserved.

6 Empirical analysis

6.1 Preliminary analysis and validity of the empirical model

In what follows I discuss very briefly the important evidence, reported for the sake of brevity in the on-line Appendix A1 and B1, on the validity of the model, on its graphical analysis and its estimation allowing for heterogeneous effects across regions of birth.

The main assumption of the research design is the absence of precise sorting related to the age at which job entry as apprentices occurs (if occurs). The same assumption on the other source of random variation is trivially satisfied. In fact, individuals cannot have precise manipulation over their year of birth. To validate the analysis I follow Lee and Lemieux (2010). I consider in the age range between 25 and 35 years of age (measured as deviations from 30) all individuals who have started a job spell of at least one day in a given year of the sample period. For each region of birth, I plot the density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of the difference in discontinuity regression model on permanent employment probability. This suggestive evidence builds on the Bayes' Rule.[10]. In fact, there is not precise control over the age at which the apprenticeship labor contract occur when $Pr[a|X = x, U = u]$ is identical on either side of the cutoff in the limit of the threshold. Putting it differently, the distributions of U, V conditional on age are not truncated in age if there exist a certain degree of randomness in the sorting process.[11] For each region of birth, consistently with a treatment that is locally randomized, the histograms indicate that the conditional distributions of observed and unobserved charac-

[9] These results are available upon request from the author.

[10] That is, $Pr[X = x, U = u|A = a] = Pr[a|X = x, U = u] \frac{Pr[X=x,U=u]}{Pr(a)}$, where $Pr(a)$ and $Pr[a|X = x, U = u]$ are marginal and conditional densities

[11] Although, the graphs plot the density of V rather than the density of age, these graphs provide the same informational contents since the two distributions are equivalent up to a translation shift.

teristics on either side of the age cutoff in the limit of the threshold do not differ.[12] Hence, the conditional independence assumption holds.

I compute and graph the raw difference in means between treated and untreated cohorts of the outcome variable (permanent employment probability, apprenticeship probability and employment probability) for each of the ten values of the discrete assignment variable, age in each region. Here region is defined as the region where the worker was born and where he/she likely grew up. A drawback of the data is that I have not information on the timing of individuals' mobility before 2009. Individuals born outside Italy belong to a hypothetical 21st region. The graphical analysis is important since it gives a rough sense of the relationship and the shape of the age profile of the difference in the outcome variable before and after the labor market reform in each region of birth. In these graphs I superimpose the fit of the third order polynomial in age (99% confidence intervals). The Figure indicates that locally, ± 1 year around the age cutoff, the linear model specification is likely to be supported by the data. In fact, the estimated parameter perfectly matches the raw data. These plots reveal the existence of an instantaneous difference in discontinuity positive impact on the apprenticeship probability for the large majority of the Italian regions with the exception of Trentino Alto Adige, Molise, Sardegna, Umbria and Valle d'Aosta. Consistent results are obtained if I consider the region where individuals work.[13] This is reassuring since it implies that the randomized source of variation that I am exploiting to unpack regional disparities in apprenticeship and permanent employment rates stems from the random assignment of individuals to regions at birth. The interpretation of this finding points to the importance of the informational costs of apprenticeships that are smaller for individuals born in the same region where they work. The regions, that failed to increase the apprenticeship rate of cohorts treated by the labor market reform at the age threshold compared to the apprenticeship rate of similar untreated individuals, rather than reflecting a North-South divide, have in common the small dimension of their labor markets. The graphs also clearly indicate regional disparities in the intensity of the positive impact on the apprenticeship rate and the extent to which this impact translates into difference in discontinuity for the permanent employment probability. There is not instead graphical evidence on a difference in discontinuity effect on the employment probability.

[Figure 2 about here]

Figure 2 instead displays how the number of active firms distributes over the Italian regions. Different colors refer to different quartiles of the distribution: from the lightest to the darkest blue. The size of the regional markets plays a role with smaller (or with low population density) regions sitting in the lowest quartile. From this angle, the North-South divide does not clearly emerge. In the on-line Appendix, I present the regional distribution of the number of active firms by sectors and firm size. It is also reported the regional distribution of sectoral share of value added. It is clear that the southern (and Trentino) regions have the highest share of value added in agriculture. Nevertheless, the overall regional distribution of the number of active firms is quite similar to those that decompose it by firms size and sectors. This might implies that the number of firms with long-term production opportunities matters more than either firm size nor sectoral compositions to explaining regional disparities in apprenticeship and permanent employment rates. In

[12]Further preliminary tests on the parametric model specification and tests on the balancing-out of covariates are available upon request from the author. All this evidence supports the regression design and it is not reported to save space.

[13]These results are available upon request from the author.

contrast, the North-South divide appears looking at panel (b) of the same Figure. All the southern part of Italy, including main islands, is below the median value of the distribution of the percentage of students who scored the highest level in math PISA tests.[14]

These figures set the premises and constitute good grounds for what follows. Unpacking these geographic variations in regional educational institutions and in the average characteristics of the firms in a region could be important to understand the extent to which a labor contract committed to a human capital investment creates a job match that persists over time.

6.2 Estimation results

As discussed above, automatic conversion rates into standard permanent labor contracts of apprenticeships is quite heterogeneous across Italian regions. The 2012 labor market reform sets nationwide rules on the basis of which it is not obvious that differences across the regions where the workers were born arise. Yet, the region of birth in the majority of cases constitutes the environment where the individual grew up and was educated. The current literature on the determinants of a labor contract which increases human capital has mainly emphasized the role of commitment (Dustmann and Schönberg 2012) to the training provision in a framework of asymmetric information (Acemoglu and Pischke 1998, Acemoglu and Pischke 1999). In such a setting the commitment to the human capital investment constitutes a necessary requirement. The successfulness of the apprenticeship labor contract to serve as a port of entry into permanent employment could also depend on whether and to what extent the complementarities between the on-the-job human capital accumulation and the individual's competencies and skills are related to the sorting of the individuals and to the screening of the firms in a given job. These sorting-screening processes could be driven by signals which are observable. The general education level, and where it was achieved, stands above all the other signals. If this true, the educational and other observational signals of the migrants could be much weaker than that of the locals because firms are much better informed on the educational and environmental context of the region where they operate. All in all, this evidence points to the importance of the informational content of the apprenticeship labor contract suggesting that the observational signals of those born in the region where the firm operates are stronger.[15]

I use ISTAT data on the regional percentage of those, aged 15, who scored the maximum (minimum) level in the PISA test in mathematics and reading. These percentages are then averaged out over time (2006-2015). Quality of the upper secondary education system is higher (lower) the higher the quartiles of the distribution of these regional percentages.[16] Figure (3) suggests that this let the sorting-screening processes of individuals and firms be more successful because asymmetric information are reduced and, possibly, because there could be complementarities between former education and the on-the-job human capital accumulation process. In fact, the difference in discontinuity effects on the outcomes of interest varies across quartiles of the distribution of the percentage of those

[14]Similar pictures can be provided for the PISA reading test and for the distribution of students who scored the minimum level in these tests. In such a case, all southern regions are above the median of the distribution.

[15]The distance between the individual's hometown and the location of the workplace might be negatively correlated with the power of the signal. Hence, I cannot exclude that there is important geographic variation within regions that I am unable to account for. This is because I have only information at regional level.

[16]Even though students involved in these tests are younger than those considered in my analysis, this might not be an issue. In fact, what is relevant to the analysis that will follow is the regional ranking (quartiles of the distribution of the average regional score) that is quite stable over time.

who scored the maximum (minimum) level in math test. Clearly, the lowest quality is associated to the smallest ITT impact on the apprenticeship rate. Moreover, the permanent employment probability at the age cutoff of treated individuals compared to the permanent employment rate of those untreated are not statistically different when the regional quality of the education system is low. Similar results, reported in the on-line Appendix, can be found when I use the score in the reading performance test. This evidence suggests that it is more likely that the apprenticeship labor contract serves as a stepping stone into permanent employment in a context where the quality of the former education system is not too low. If this is the case, the same individual with the same observable characteristics would increase more her productivity in a firm rather than in another. Consequently, disparities across regions emerge because the strength of these complementarities differs across regions and some regions could experience larger permanent employment gains than others.

[Figure 3 about here]

Moreover, in regions, where the quality of the regional education system is higher, these complementarities amplify the initial advantages leading to a higher permanent employment gain over time. Figure (4) shows that after 30 months from the baseline, the positive dynamic ITT impact associated to the regions with the lowest educational performance is equal to 4% and it doubles to about 8% for the regions with the highest educational achievements.[17] There is a clear mapping of the North-South divide on the impacts on permanent employment with the North-South strong divide in schooling performances. For instance regions that have the highest (lowest) percentage of students who just scored the maximum (minimum) level in the math test are: Trentino Alto Adige, Friuli Venezia Giulia, Lombardia and Veneto (Basilicata, Calabria, Campania, Puglia, Sardegna and Sicilia). This North-South divide dualise further the Italian dual labor market.

[Figure 4 about here]

One could argue that definite conclusions cannot be drawn on the sole basis of the PISA test scores. In fact, there is an ample literature showing that the PISA score tests do not really reflect the underlying quality of the education system, due to several reasons (see, inter alia Araujo, Saltelli and Schnepf (2017), or Hopfenbeck, Lenkeit, El Masri, Cantrell, Ryan and Baird (2018) for some recent evidence). To avoid that conclusions based on the assumption of differences in the regional education systems could be wrong due to a rather imperfect education quality measure, in the on-line Appendix I explore alternative measures of the regional quality of the education. I use ISTAT regional data on the percentage of those who repeat the schooling year, the average number of enrolles per class and the average number of enrolles per school in upper secondary education, the average dropout rate in upper secondary education.[18] The main message of the paper does not change. Moreover, the geographic variation in PISA math test scores maps better

[17] The size of this differential is consistent if education quality is instead measured by the lower percentage of those scoring the minimum level in the PISA math test.

[18] The percentage of those repeating the schooling year is calculated as the number of those who repeat the schooling year over the total number of enrolles at upper secondary school in a given region; the average number of enrolles per class is calculated as the total number of enrolles over the total number of classes in a region, the average number of enrolles per school as the total number of enrolles over the total number of schools in a region, the regional share of dropout rate is calculates as the total number of students who dropout over the total number of enrolles in upper secondary education.

than the other indicators the North-South divide in permanent employment gains in the medium-run. Hence, these robustness checks are also helpful to show that PISA test scores are the best indicators of the quality of the regional education system. This is possibly because these test scores better capture unobservable complementarities between former education and later on-the-job training.

Nevertheless, this interpretation fails to fully explain why the static impact on the apprenticeship labor contract is statically not different from zero when the dimension of the regional labor market is limited (Trentino Alto Adige, Molise, Sardegna, Umbria and Valle d'Aosta). Hence, I consider some characteristics of the regional labor market which could work as a barrier to increase the quantity of the apprenticeship labor contracts. The number of productive firms with expected long-term production opportunities in a region could fix the quantity of the apprenticeship labor contracts by limiting the successfulness of the screening of the firms and the sorting into apprenticeships of the workers. In fact, considering the framework presented by Cahuc et al. (2016), the lower the number of productive firms, the lower the expected production opportunities, the higher the number of temporary job contracts which are created to fulfill these production opportunities with short expected durations. I use the AIDA (Bureau van Dijk) database to determine the number of firms with a non-missing record on total revenues in each region from 2010 to 2014. These amounts are averaged out across time to possibly smooth out excess of variability in this number. I then draw the distribution of the resulting quantities assigning a value equal to 1 to the quartile of the distribution to which the region belongs.

[Figure 5 about here]

Figure (5) clearly shows that the static effect on the apprenticeship rate is lower at the lowest quartiles albeit it is not much different from the one estimated at the fourth. However, heterogeneous behavior emerges when looking at the impact on permanent employment.[19] In fact, there are no difference in discontinuity effects on permanent employment for those regions that are characterized by a lower (compared to the other regions) number of active firms. Therefore, the dimension of the regional labor market can be a barrier to the quantity of potential successful apprenticeship labor contract. In the on-line Appendix I show the robustness of this finding using other indicators of the regional production system (the number of active firms in the ISTAT regional database, the variance of the regional distribution of non-missing total revenues of firms recorded in AIDA, the regional average turnover rate of the firms, the proportion of high tech firms in a region, the share of employees in high tech firms over the total number of employees in a region). This robustness check also points to the importance of the presence of high tech firms in a region.

6.3 Do regional variations in education and production systems explain geographic variations in workers and firms fixed effects?

Figure (1) displays a North-South divide in the distributions of workers and firms fixed effects in the sub sample of good workers. The North-South divide is also a feature of the distributions of PISA test scores. To investigate further this issue, figure 6 shows a plot of the quantiles of the distribution of the worker fixed effects obtained from estimating equation 1, comparing the quantile of individual fixed effects located in regions that sit

[19]The instantaneous ITT impact on the apprenticeship rate for the second and third quartiles matches the effect on the permanent employment while it is lower for the fourth quartile.

the highest quartile of the distribution of the percentage of students scoring the maximum level in the PISA math test (x axis) against the quantiles of the distribution of these individual fixed effects located in the remaining regions (y axis). Points on the right-hand side of the 45 line mean that the values of the distribution on the X axis are higher than those of the distribution on the Y-axis. Since many points are on the right-hand side of the main diagonal, it seems reasonable to conclude that employees working in region where the quality of the upper secondary schooling system is high have higher unobserved ability for given observable characteristics. These skills and competencies when adopted in a good firm environment, likely interact with skills and competencies that are developed by on-the job training.

[Figure 6 about here]

Below I revisit this question in a regression framework and again conclude that the education and production system matters for the creation of a job position that persists over time. In fact, as a final remark one could argue that production and education systems should be treated jointly, and not in isolation. There could be potential interactions between both systems that could affect the outcome of the apprenticeship contract reform.

[Table 1 about here]

Tables (1) and (2) show the regions that sit both in the highest quartile of the percentage of those who scored the maximum level in the math PISA test and in the highest quartile of the distributions of the number of active firms benefit of the highest permanent employment gains. This evidence holds true instantaneously (i.e. static effect) and it strengthens further over time (i.e. after 30 months from the baseline). Overall, when interacted with the characteristics of the production system, the indicator of the education system that performs best is the PISA math test score. For instance, the static difference in discontinuity impact on permanent employment probability is positive for all the indicators of school quality, albeit these are not relevant factors when interacted with the number of high tech firms in the region. Hence, skills and competencies tested by the PISA tests at upper secondary schools are most likely to predict the future pattern of the individual's occupational prospects.

[Table 2 about here]

In sum, on the one hand the quantity of the potential successful jobs is limited by a fixed number of productive firms. On the other hand, when the quality of the education system is low, the capacity of the apprenticeship labor contract to serve as a stepping stone into permanent employment is limited. As a result, geographic variations in permanent employment rates stems from geographic variations in the education and production systems.

7 Conclusions

In this study I analyze the relationship between the geographic variation in apprenticeship and consequent permanent employment rates and the geographic variation in the regional education and production systems. I seek to unpack these geographic variations to investigate under which circumstances a labor contract, committed to the provision of human

capital investment, succeeds in creating a job match that persists over time. I do this by using a very rich administrative dataset by the Italian Ministry of Labor and Social Policies, ($CICO$). The approach is innovative in its granular specificity to the study of static and dynamic permanent employment rate in the analysis of the particular regional environment associated with these differences. To my knowledge, this is the first study that empirically measures the geographical differences in permanent jobs created by a costly human capital investment across an array of different types of indicators of the quality of the education and production systems that might explain these distinctions. In my research design, I exploit the randomized variability introduced by a labor market reform at the age cutoff of 30 years, above which job entry as apprentice is not possible. On the basis of this unique setting, the conditional independent assumption between the location of work and this randomized variability holds. On the top of that, I exploit the random assignment of individuals to regions at birth. I find that the Italian North-South divide in the quality of general education maps into and further amplifies the North-South divide in labor market performances. This is possibly because of the existence of complementarities between former education and on-the-job human capital accumulation. These complementarities are a necessary but not sufficient condition to create apprenticeship job positions that translate into occupations that persists over time. In fact, the limited number of active firms with expected long-term employment opportunities in a region is a barrier to the quantity of job entries as apprentices. However, this rich administrative dataset contains information at the region of work and region of birth level only. It is likely that a comprehensive view of the economic geography of permanent job creation requires a within region analysis that integrates this across regions evaluation. This challenging project is left to future research.

References

Acemoglu, D. and Pischke, J.-S. (1998). Why do firms train? theory and evidence, *The Quarterly Journal of Economics* **113**(1): 79–119.

Acemoglu, D. and Pischke, J.-S. (1999). Beyond becker: Training in imperfect labour markets, *Economic Journal* **109**(453): F112–42.

Araujo, L., Saltelli, A. and Schnepf, S. V. (2017). Do pisa data justify pisa-based education policy?, *International Journal of Comparative Education and Development* **19**(1): 20–34.

Blanchard, O. and Landier, A. (2002). The perverse effects of partial labour market reform: fixed-term contracts in france, *Economic Journal* **112**(480): F214–F244.

Boeri, T. and Garibaldi, P. (2007). Two tier reforms of employment protection: a honeymoon effect?, *Economic Journal* **117**(521): 357–385.

Booth, A., Francesconi, M. and Frank, J. (2002). Temporary jobs: Stepping stones or dead ends?, *Economic Journal* **112**(480): F189–F213.

Brunello, G. and De Paola, M. (2008). Training and economic density: Some evidence form italian provinces, *Labour Economics* **15**(1): 118–140.

Cahuc, P., Charlot, O. and Malherbet, F. (2016). Explaining the spread of temporary jobs and its impcat on labour turnover, *International Economic Review* **57**: 533–572.

Cahuc, P. and Postel-Vinay, F. (2002). Temporary jobs, employment protection and labor market performance, *Labour Economics* **9**(1): 63–91.

Cappellari, L., Dell'Aringa, C. and Leonardi, M. (2012). Temporary employment, job flows and productivity: A tale of two reforms, *Economic Journal* **122**(562): F188–F215.

Combes, P.-P. and Duranton, G. (2006). Labour pooling, labour poaching, and spatial clustering, *Regional Science and Urban Economics* **36**(1): 1–28.

Combes, P.-P., Duranton, G., Gobillon, L., Puga, D. and Roux, S. (2012). The productivity advantages of large cities: Distinguishing agglomeration from firm selection, *Econometrica* **80**(6): 2543–2594.

Dal Bó, E., Finan, F. and Rossi, M. (2013). Strengthening state capabilities: The role of financial incentives in the call to public service, *The Quarterly Journal of Economics* **128**(3): 1169–1218.

Doeringer, P. and Piore, M. (eds) (1971). *Internal Labor Markets and Manpower Adjustment*, D.C. Heath and Company.

Dolado, J. (2017). Eu dual labour markets: Consequences and potential reforms.

Dustmann, C. and Schönberg, U. (2009). Training and union wages, *The Review of Economics and Statistics* **91**(2): 363–376.

Dustmann, C. and Schönberg, U. (2012). What makes firm-based vocational training schemes successful? the role of commitment, *American Economic Journal: Applied Economics* **4**(2): 36–61.

Gathmann, C., Helm, I. and Schönberg, U. (forthcoming). Spillover effects of mass layoffs, *Journal of the European Economic Association* .

Greenstone, M., Hornbeck, R. and Moretti, E. (2010). Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings, *Journal of Political Economy* **118**(3): 536–598.

Heinrich, C., Mueser, P. and Troske, K. (2005). Welfare to temporary work: Implications for labor market outcomes, *The Review of Economics and Statistics* **87**(1): 154–173.

Holmlund, B. and Storrie, D. (2002). Temporary work in turbulent times: The swedish experience, *Economic Journal* **112**(480): F245–F269.

Hopfenbeck, T. N., Lenkeit, J., El Masri, Y., Cantrell, K., Ryan, J. and Baird, J.-A. (2018). Lessons learned from pisa: A systematic review of peer-reviewed articles on the programme for international student assessment, *Scandinavian Journal of Educational Research* **62**(3): 333–353.

Ichino, A., Mealli, F. and Nannicini, T. (2008). From temporary help jobs to permanent employment: what can we learn from matching estimators and their sensitivity?, *Journal of Applied Econometrics* **23**(3): 305–327.

Lazear, E. P. (1990). Job security provisions and employment, *The Quarterly Journal of Economics* **105**(3): 699–726.

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics, *Journal of Economic Literature* **48**(2): 281–355.

Macho-Stadler, I., Perez-Castrillo, D. and Porteiro, N. (2014). Coexistence of long-term and short-term contracts, *Games and Economic Behavior* **86**: 145 – 164.

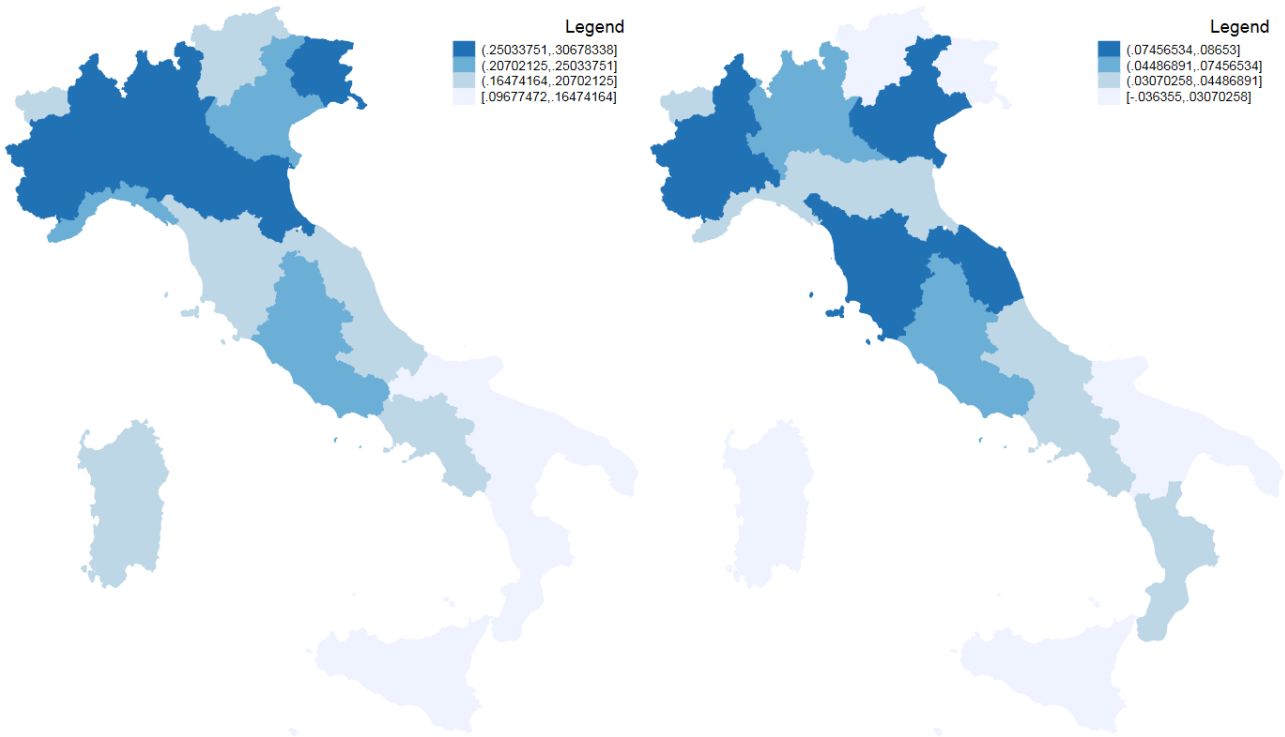
Manning, A. and Petrongolo, B. (2017). How local are labor markets? evidence from a spatial job search model, *American Economic Review* **107**(10): 2877–2907.

Muehlemann, S. and Wolter, S. C. (2008). Regional effects on employer-provided training: Evidence fromapprenticeship training in switzerland, *Zeitschrift fr Arbeitsmarkt-tForschung - Journal for Labour Market Research* **40**(2/3): 135–147.

Serafinelli, M. (forthcoming). *Good* firms, worker flows and local productivity, *Journal of Labor Economics* .

Regional variation in apprenticeship and permanent employment rates: which causes?

1 Figures

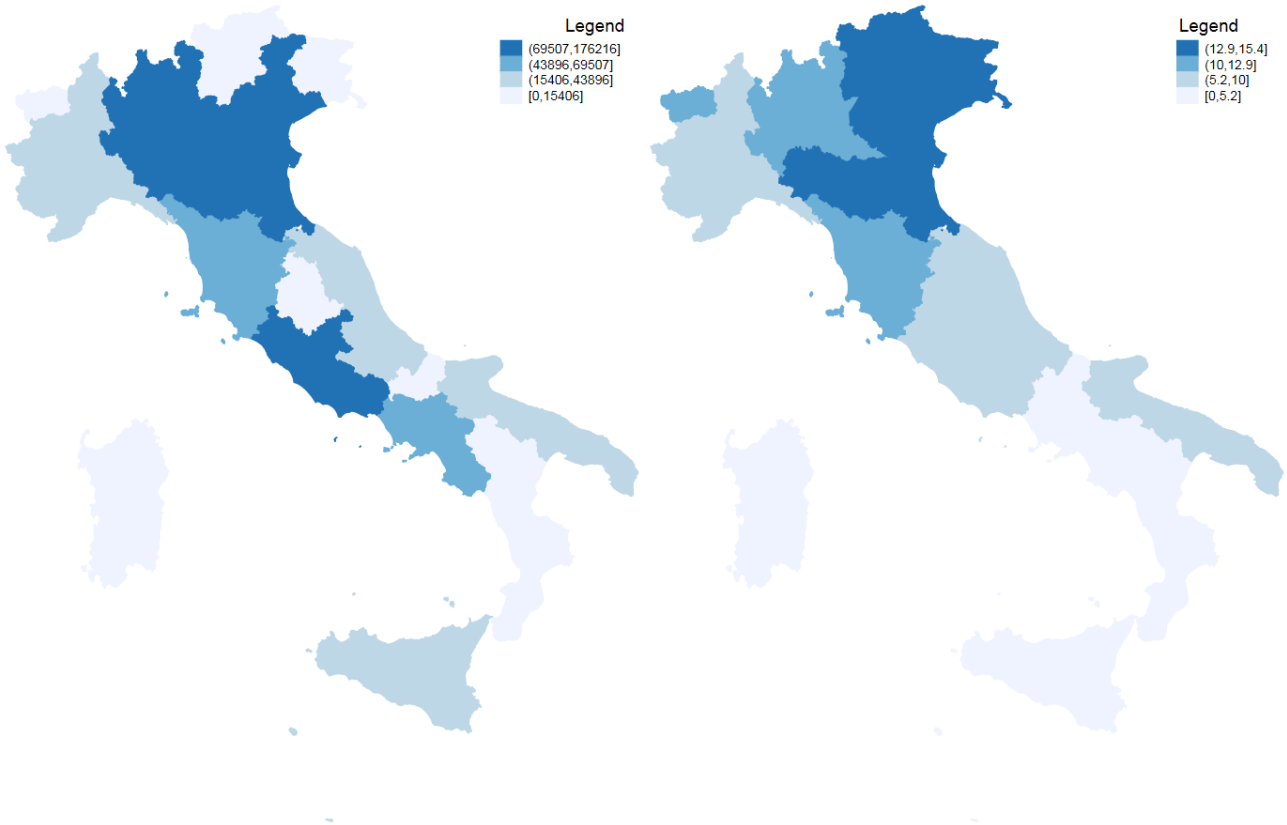


(a) Individual fixed effects

(b) Firms fixed effects

Notes: Firm and individual effects that are obtained estimating equation (4) for the period January 2010-December 2014. The two panels show the geographic variations across regions of work in workers and firms fixed effects for the sub-sample of good workers. Good workers are define as those above the 67th percentile of the individual fixed effects distribution.

Figure 1: Geographical variations in worker and firm fixed effects: across regions of work

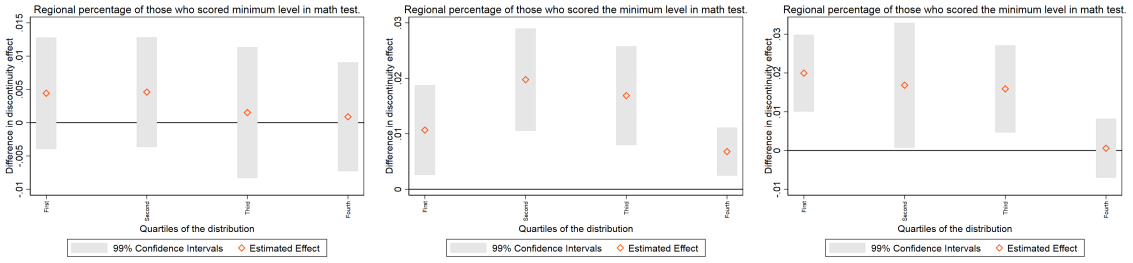


(a) Number of active firms in a region.

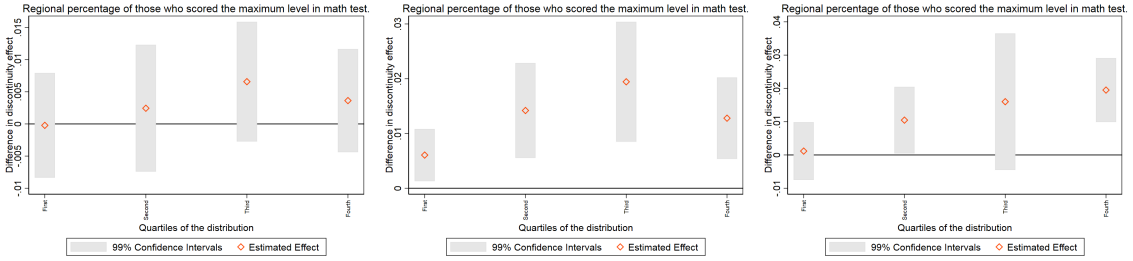
(b) Percentage with high scores in math PISA test

Notes: Data source: Aida and Italian Statical Office.

Figure 2: Geographical variations in the number of active firms in a region and the average regional PISA high test scores in math

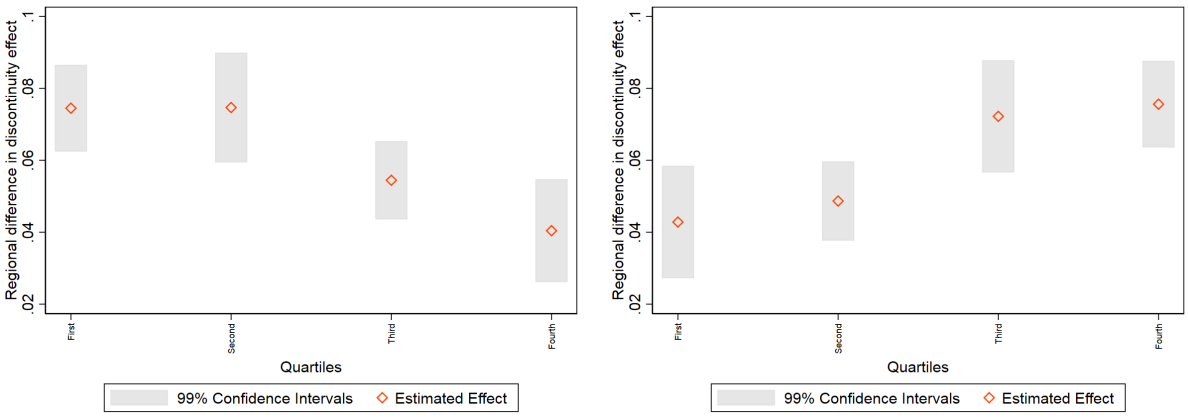


(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.



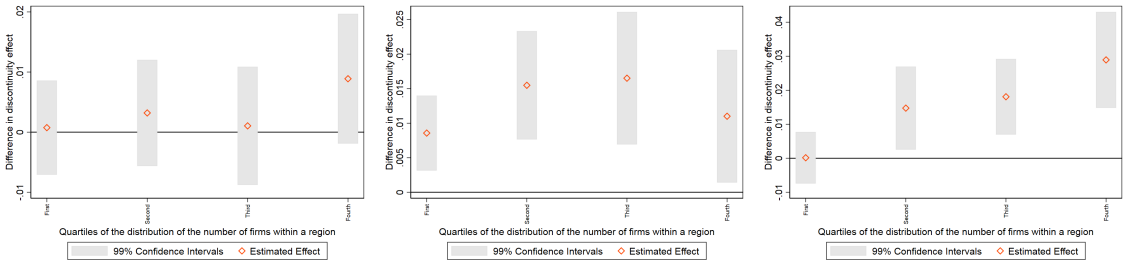
(d) Employment Prob. (e) Apprenticeship Prob. (f) Permanent employment Prob.

Figure 3: Differential impact at the baseline across the distribution of the regional percentage of high (low) level of math PISA test scores



(a) Minimum level math. (b) Maximum level math.

Figure 4: Differential permanent employment probability gains after 30 months from the baseline across the distribution of the regional percentage of high (low) level of math PISA test scores



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

Notes: Data source: AIDA. The dimension of the regional labor market is measured by the average number of firms in a region with non missing records on total revenues between 2010 and 2014.

Figure 5: Difference in discontinuity: differential impact across the dimension of the regional labor market

2 Tables

	Permanent employment	
	Non-high interaction	High interaction
High number of firms and high math score	0.009	0.019
	0.003	0.005
	[0.001-0.017]	[0.007-0.030]
High firms' turnover rate and high math score	0.011	0.016
	0.003	0.005
	[0.003-0.019]	[0.003-0.028]
High employment rate in high tech and high math score	0.009	0.021
	0.003	0.006
	[0.001-0.017]	[0.007-0.035]
High number of high tech firms and high math score	0.011	0.019
	0.003	0.007
	[0.003-0.018]	[0.001-0.037]
High number of high tech firms and low repeating schooling year rate	0.012	0.012
	0.003	0.017
	[0.005-0.019]	[−0.031-0.055]
High number of high tech firms and low ratio of n. students per class	0.012	0.002
	0.003	0.012
	[0.005-0.019]	[−0.028-0.033]
High number of high tech firms and low dropout rate in upper secondary schools	0.012	0.007
	0.003	0.013
	[0.005-0.019]	[−0.027-0.041]
High number of high tech firms and low ratio of n. students per school	0.010	0.017
	0.003	0.005
	[0.002-0.019]	[0.004-0.031]

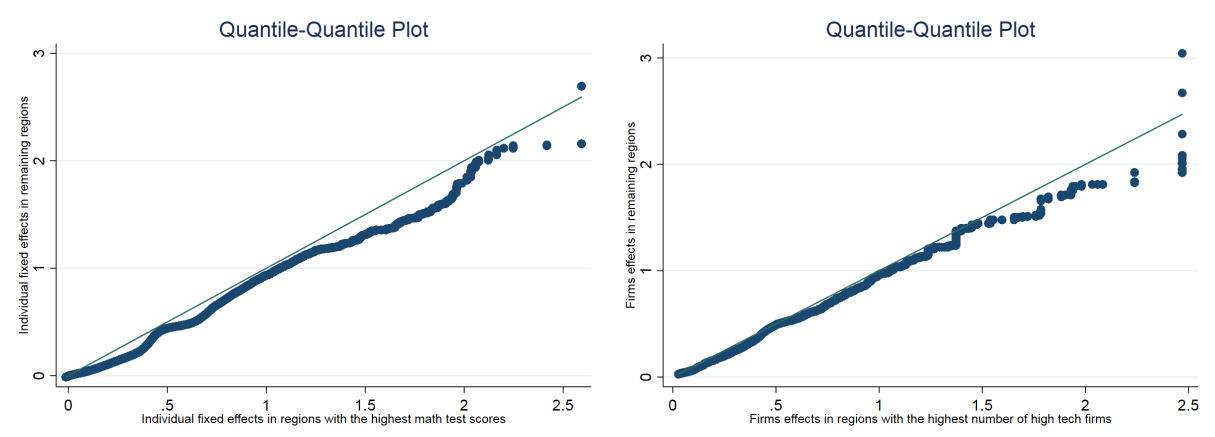
Notes: (Non)-High interaction is a dummy variable that takes the value of 1 (0) if the region sits both in the highest quartile of the quality indicator of the upper secondary school system (i.e. in the lowest quartile when higher quality is associated to a lower value of the indicator, such as for instance the case of the dropout rate) and in the highest quartile of the distribution of characteristics of the production system (such as for instance the number of active firms).

Table 1: Difference-in-discontinuity impact on permanent employment: interaction between education quality and production system.

	Permanent employment	
	Non-high interaction	High interaction
High number of firms and high math score	−0.073	0.174
	0.043	0.048
	[−0.183-0.038]	[0.052-0.297]
High firms' turnover rate and high math score	−0.059	−0.261
	0.043	0.064
	[−0.168-0.051]	[−0.426-−0.097]
High employment rate in high tech and high math score	−0.043	0.155
	0.043	0.039
	[−0.154-0.067]	[0.055-0.256]
High number of high tech firms and high math score	−0.032	0.128
	0.041	0.049
	[−0.137-0.072]	[0.003-0.253]
High number of high tech firms and low repeating schooling year rate	−0.004	−0.079
	0.038	0.169
	[−0.101-0.092]	[−0.511-0.354]
High number of high tech firms and low ratio of n. students per class	−0.008	−0.200
	0.035	0.310
	[−0.098-0.083]	[−0.994-0.593]
High number of high tech firms and low dropout rate in upper secondary schools	−0.004	−0.039
	0.036	0.143
	[−0.096-0.089]	[−0.404-0.326]
High number of high tech firms and low ratio of n. students per school	−0.026	0.038
	0.043	0.043
	[−0.137-0.085]	[−0.071-0.148]

Notes: (Non)-High interaction is a dummy variable that takes the value of 1 (0) if the region sits both in the highest quartile of the quality indicator of the upper secondary school system (i.e. in the lowest quartile when higher quality is associated to a lower value of the indicator, such as for instance the case of the dropout rate) and in the highest quartile of the distribution of characteristics of the production system (such as for instance the number of active firms).

Table 2: Dynamic difference-in-discontinuity impact on permanent employment after 30 months: interaction between education quality and production system.



Notes:

(a) Individual fixed effects comparing regions by scores in math PISA test.

(b) Firms fixed effects comparing regions by number of high tech firms.

Shown is a quantile-quantile plot of worker and firms effects in 2010-2014.

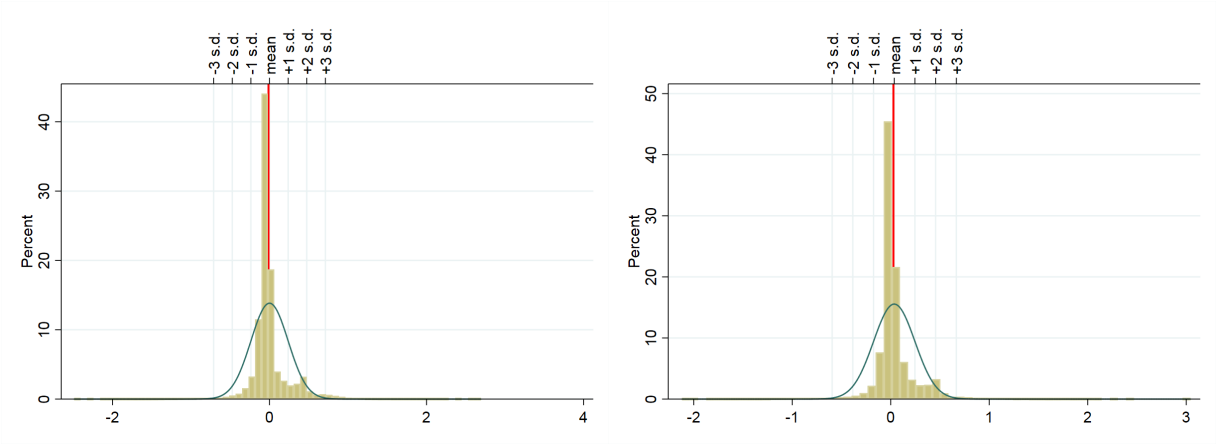
Figure 6: Quantile-quantile plot: worker and firm effects

Regional variation in apprenticeship and permanent employment rates: which causes?

Content

This appendix is organized as follows. Section A1 is devoted to present additional materials. It is first discussed whether the region of birth matters. Then it is presented an analysis on the role of the uncertainty in the regional labor market. For each region, section B1 displays the graphical analysis. Then the density plot of the residual of the age regression on covariates is reported.

A1 Additional materials

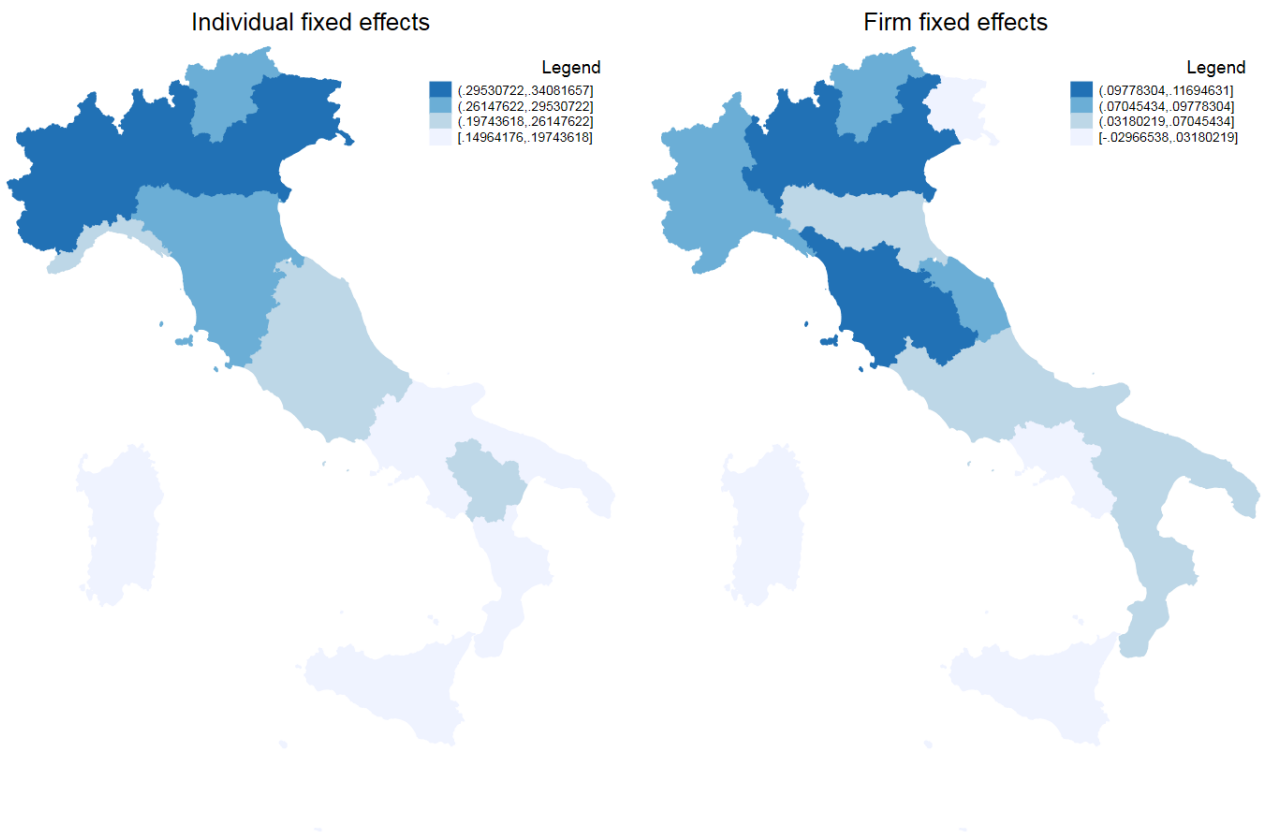


(a) Individual fixed effects

(b) Firms fixed effects

Notes: Figure A1 displays firm and individual effects that are obtained estimating equation (4) in the main text for the period January 2010-December 2014. The solid vertical line defines the 67th percentile of the individual fixed effects (-0.013) and the 67th percentile of the firm fixed effects (0.027). The second x axis reports also the mean (4.196e-17, individual fixed effect; .035, firm fixed effects) and the standard deviations of the two distributions.

Figure A1: Worker and firm fixed effects distributions.



(a) Individual fixed effects

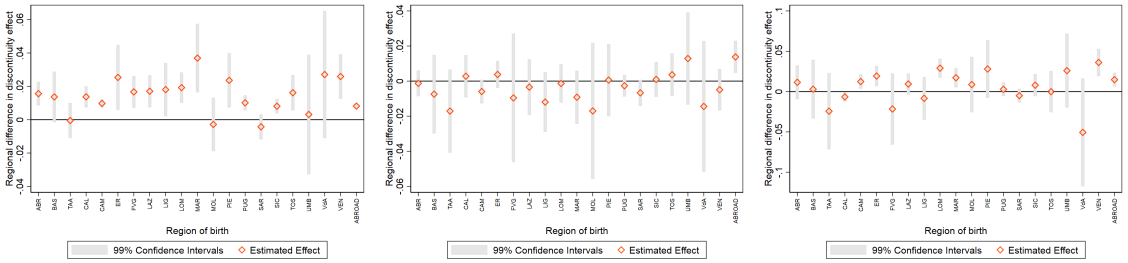
(b) Firms fixed effects

Notes: Firm and individual effects that are obtained estimating equation (4) for the period January 2010-December 2014. The two panels show the geographic variations across regions of birth in workers and firms fixed effects for the sub-sample of good workers. Good workers are define as those above the 67th percentile of the individual fixed effects distribution.

Figure A2: Geographical variations in worker and firm fixed effects: across regions of birth

A1.1 Does the environment where the individual was born matter?

In equation (1) represents the permanent employment (apprenticeship rate) rate premium of the labor market reform around the cutoff of 30 years of age. I extend the model to allow for heterogeneous impact across regions by introducing interaction terms between the difference in discontinuity parameter and the workers' region of birth dummies. These static effects are consistent with the difference in the mean values of the outcomes between treated and untreated cohorts at the age threshold illustrated in the following appendix **??**. This consistency supports the validity of the research design. Figure A3 shows that Trentino Alto Adige, Molise, Sardegna, Umbria and Valle d'Aosta are the only regions where the static ITT parameter on the apprenticeship rate is not statistically different from zero. In contrast, for Calabria, Campania, Emilia Romagna, Liguria, Piemonte, Puglia and Sicilia this impact is slightly higher than the corresponding effect estimated for those who are working in these regions independently on where they were born. This positive gain is, instead, moderate for Basilicata (the effect is statistically different from zero at 5% level), Lombardia, Marche, Valle d'Aosta and Veneto. The 21th region of birth gathers all foreign workers. For them, the static ITT impact is positive and statically different from zero. However, it is smaller when compared to the corresponding impact for individuals born in all the other Italian regions. The figure suggests also the extent to which a static positive impact on the apprenticeship rate translates into an effect on the permanent employment probability: the static ITT parameter is positive and statistically different from zero (at 5% level) for Campania, Emilia Romagna, Lazio, Lombardia, Marche, Piemonte, Veneto and for those born abroad. Overall there is no effect on the employment probability with the exception of foreign workers who could possibly be the recipients of the hiring incentive fixed by legislative decree no 76/2013.

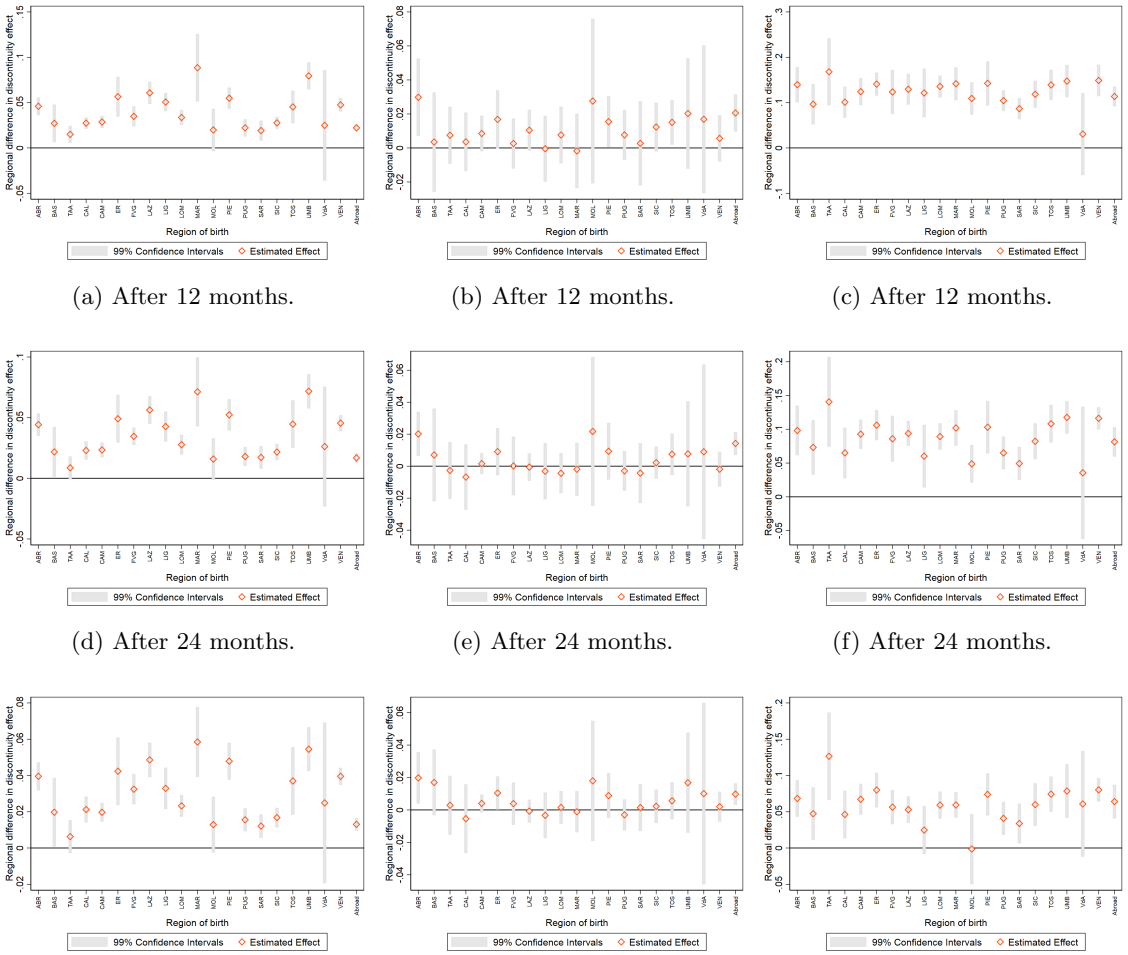


(a) Apprenticeship Prob. (b) Employment Prob. (c) Permanent Employment Prob.

Figure A3: Difference in discontinuity: differential impact across regions of birth

Figure A4 presents instead the dynamic ITT parameters on the outcomes of interest after 12, 24 and 30 months from the baseline allowing for heterogeneous effects across regions of birth. While there are no significant effects for those working in Molise, the difference in discontinuity impact on the apprenticeship probability for those who were born there, is positive and statistically different from zero after 12, 24 and 30 months. However, the corresponding positive gain in terms of permanent employment vanishes out after 24 months. Overall, individuals treated by the labor market reform at the age cutoff increased their permanent employment rate compared to untreated individuals. At 30 months from the baseline, those born in Trentino Alto Adige benefit of the highest impact on the permanent employment rate (about 12.7%) followed by Emilia Romagna, Veneto, Umbria, Piemonte and Toscana (around 8%). The difference in discontinuity medium-run impact for those born in Sardegna and Puglia is in the same order of magnitude of the

corresponding impact for those working in these regions independently on where they were born. Those who were born in Abruzzo, Trentino Alto Adige, Campania, Friuli Venezia Giulia and Sicilia (Liguria) and treated by the labor market reform at the age threshold increased their permanent employment probability more (less) than 1% compared to the corresponding impact on those working in these regions. Finally, workers born in Calabria and Basilicata gain more if they migrate but less than 1% compared to those who work in these regions.



(a) After 12 months. (b) After 12 months. (c) After 12 months.

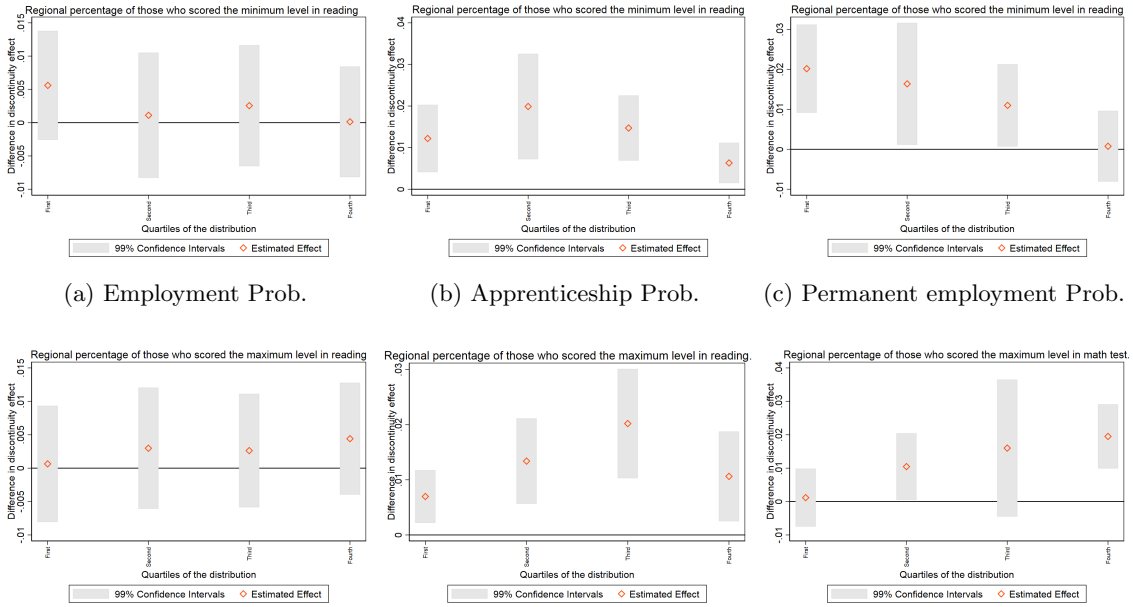
(d) After 24 months. (e) After 24 months. (f) After 24 months.

(g) After 30 months. (h) After 30 months. (i) After 30 months.

Figure A4: Difference in discontinuity: differential impact across regions of birth over time

A1.2 Robustness to other indicators of the quality of the education system

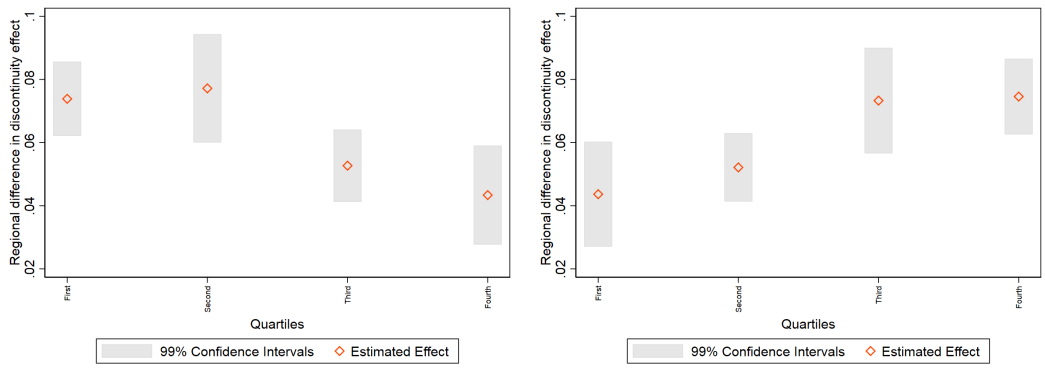
A1.2.1 Regional percentage of those who scored the highest (lowest) level in reading PISA test.



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

(d) Employment Prob. (e) Apprenticeship Prob. (f) Permanent employment Prob.

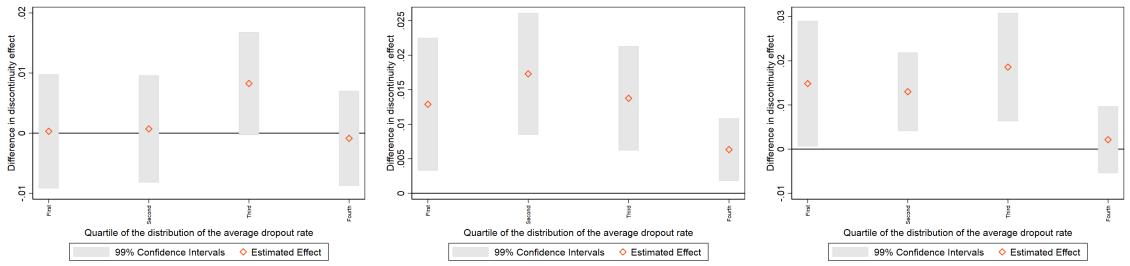
Figure A5: Differential impact at the baseline across the distribution of the regional percentage of high (low) level of reading PISA test scores



(a) Minimum level reading. (b) Maximum level reading.

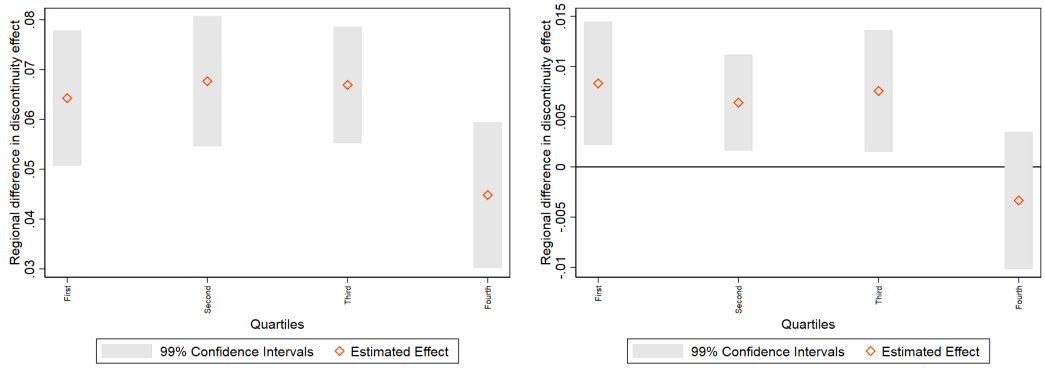
Figure A6: Differential permanent employment probability gains after 30 months from the baseline across the distribution of the regional percentage of high (low) level of reading PISA test scores

A1.2.2 Regional average dropout rate in upper secondary school



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

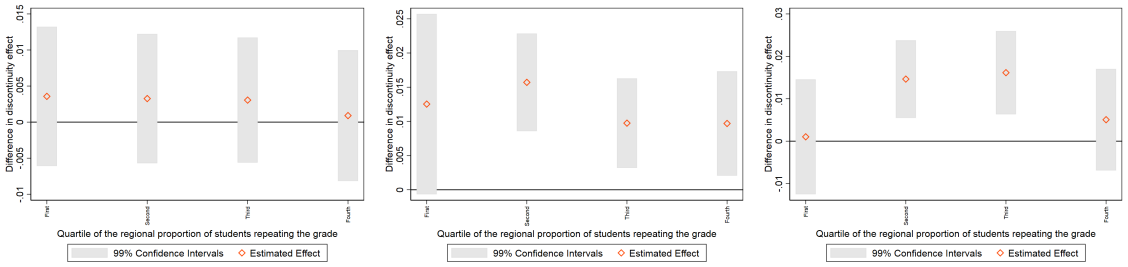
Figure A7: Differential impact at the baseline across the distribution of the regional average dropout rate in upper secondary school



(a) Permanent Employment Prob. (b) Employment Prob.

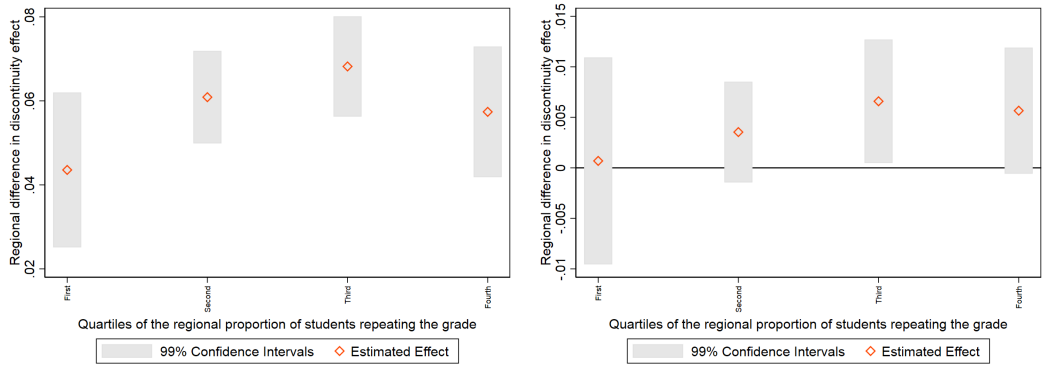
Figure A8: Differential gains after 30 months from the baseline across the distribution of the regional average dropout rate in upper secondary school

A1.2.3 Regional proportion of those who repeat the grade in upper secondary education



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

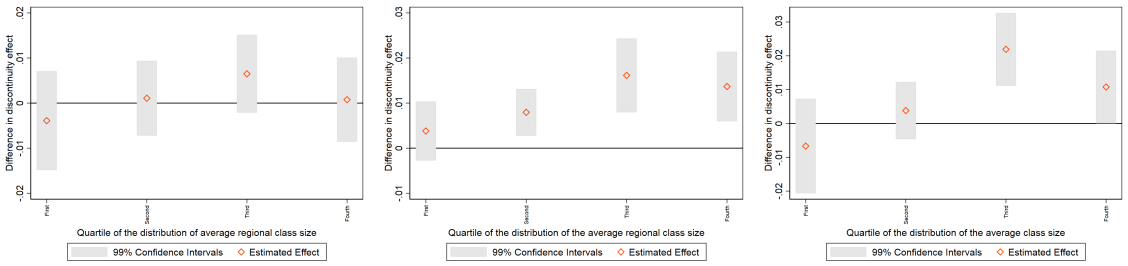
Figure A9: Differential impact at the baseline across the distribution of the regional average dropout rate in upper secondary school



(a) Permanent Employment Prob. (b) Employment Prob.

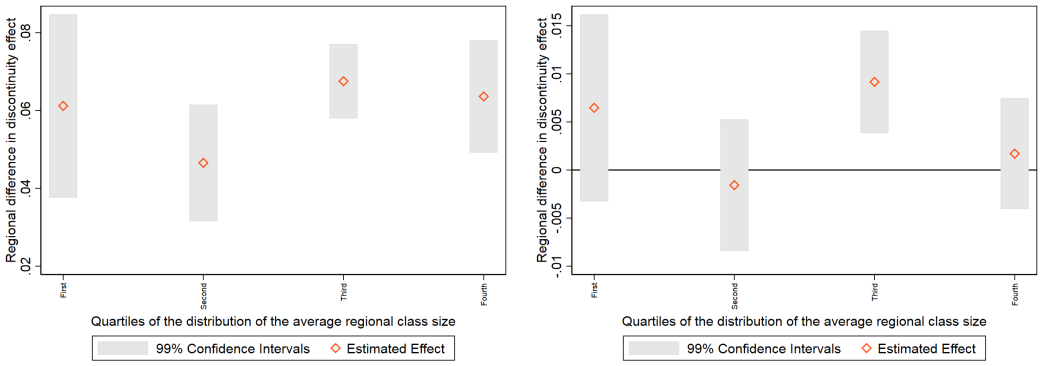
Figure A10: Differential gains after 30 months from the baseline across the distribution of the regional average dropout rate in upper secondary school

A1.2.4 Regional total number of enrolees over the total number of classes in upper secondary education



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

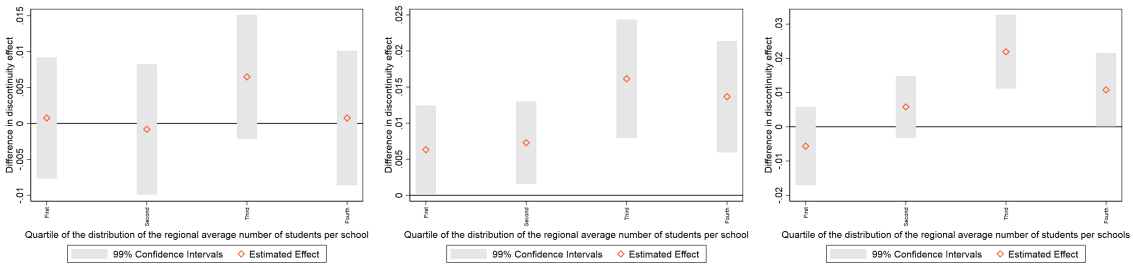
Figure A11: Differential impact at the baseline across the distribution of the regional total number of enrolees over the total number of classes in upper secondary education



(a) Permanent Employment Prob. (b) Employment Prob.

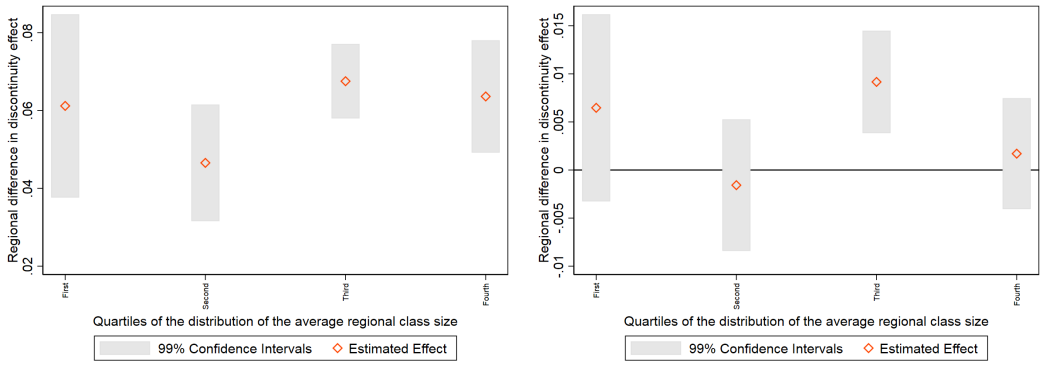
Figure A12: Differential gains after 30 months from the baseline across the distribution of the regional total number of enrolees over the total number of classes in upper secondary education

A1.2.5 Regional total number of enrolees over the total number of schools in upper secondary education



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

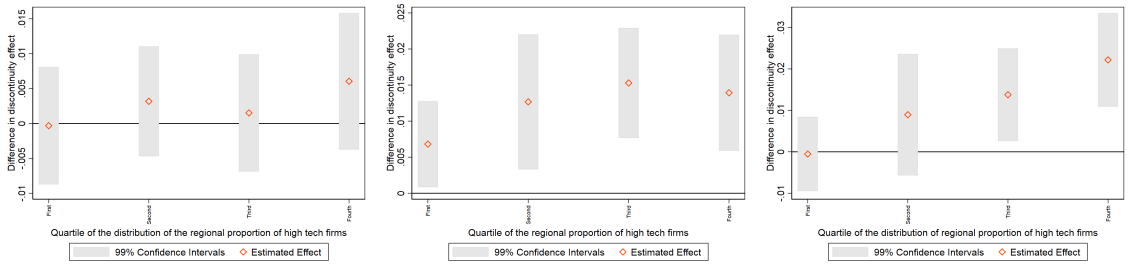
Figure A13: Differential impact at the baseline across the distribution of the regional total number of enrolees over the total number of classes in upper secondary education



(a) Permanent Employment Prob. (b) Employment Prob.

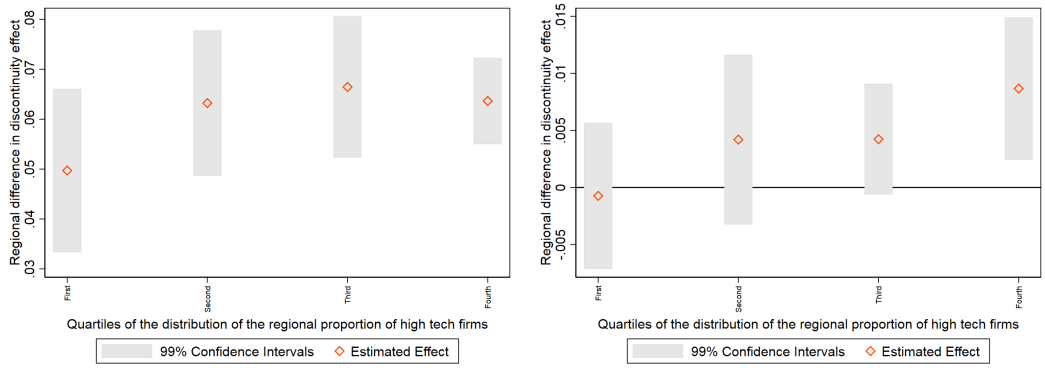
Figure A14: Differential gains after 30 months from the baseline across the distribution of the regional total number of enrolees over the total number of classes in upper secondary education

A1.2.6 Regional proportion of high tech firms



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

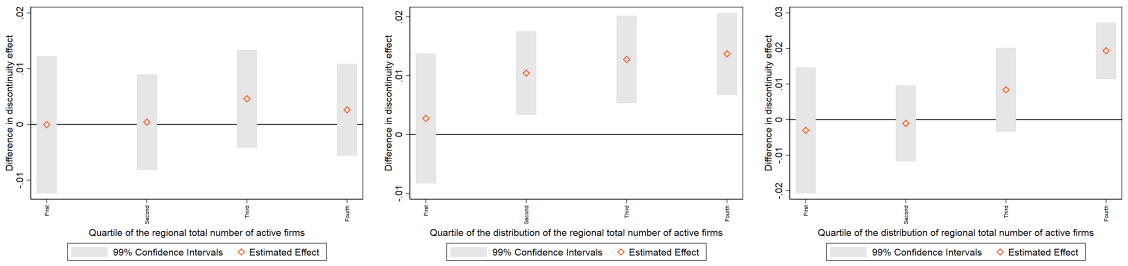
Figure A15: Differential impact at the baseline across the distribution of the regional proportion of high tech firms



(a) Permanent Employment Prob. (b) Employment Prob.

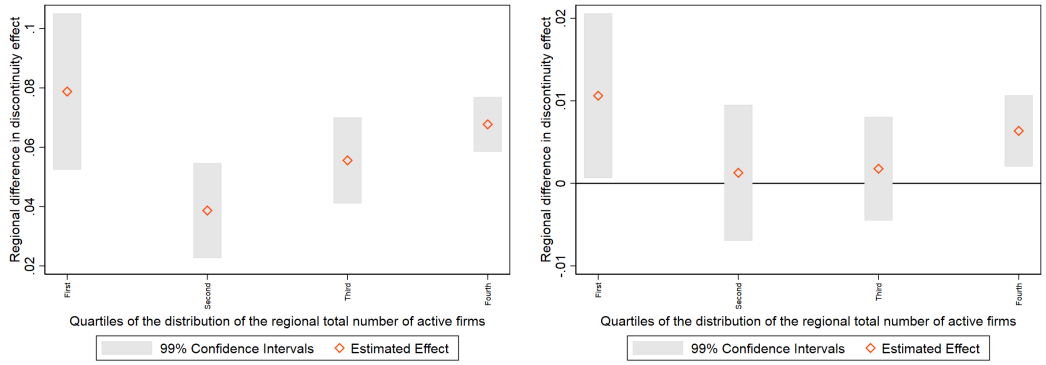
Figure A16: Differential gains after 30 months from the baseline across the distribution of the regional proportion of high tech firms

A1.2.7 Regional total number of active firms



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

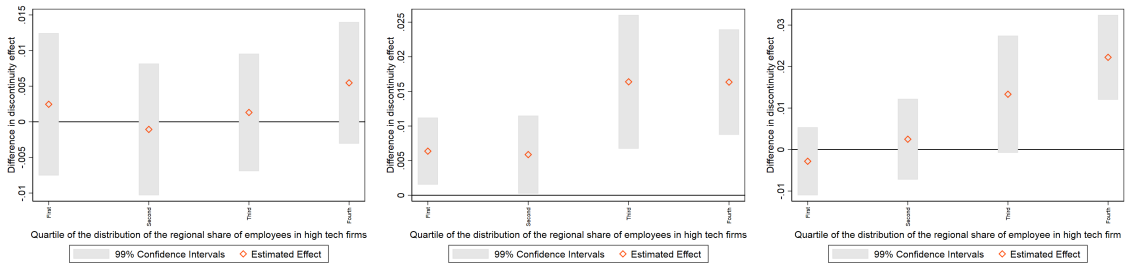
Figure A17: Differential impact at the baseline across the distribution of the regional proportion of active firms



(a) Permanent Employment Prob. (b) Employment Prob.

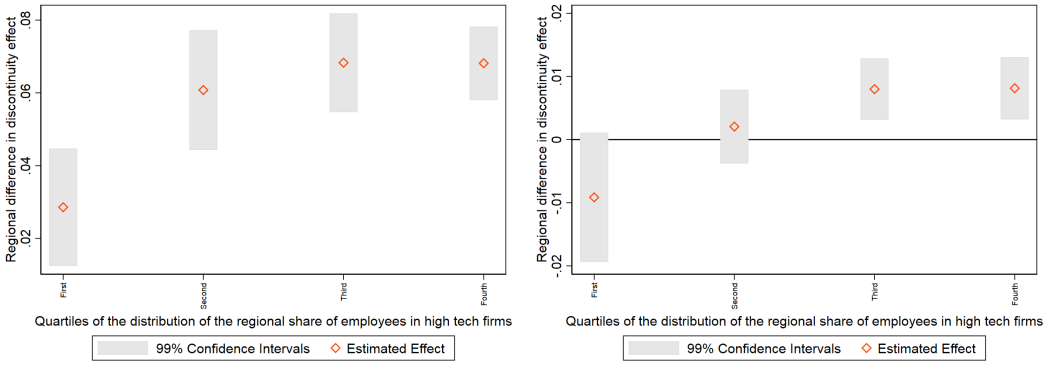
Figure A18: Differential gains after 30 months from the baseline across the distribution of the regional proportion of active firms

A1.2.8 Regional share of employees in high tech firms



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

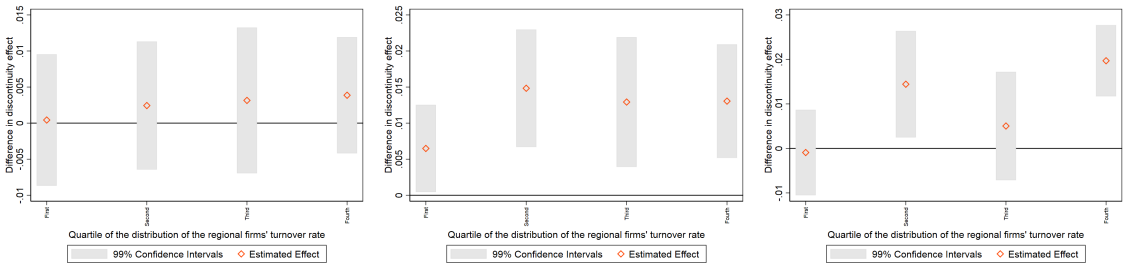
Figure A19: Differential impact at the baseline across the distribution of the regional share of employee in high tech firms



(a) Permanent Employment Prob. (b) Employment Prob.

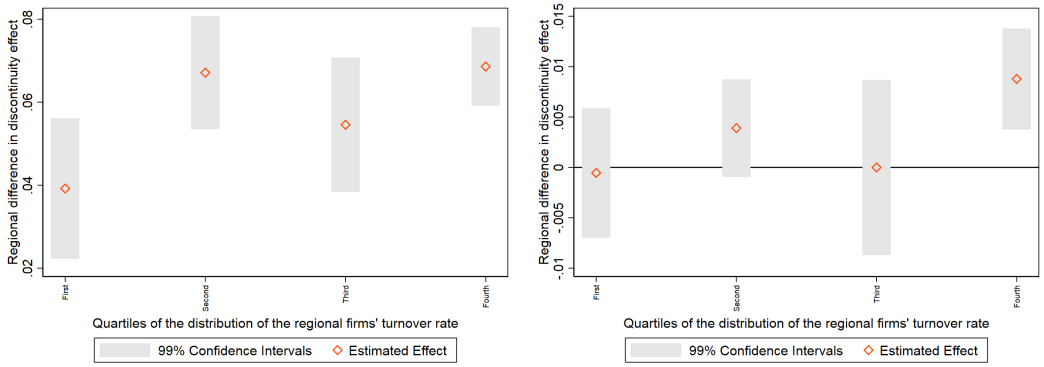
Figure A20: Differential gains after 30 months from the baseline across the distribution of the regional share of employee in high tech firms

A1.2.9 Regional firms' turnover rate



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

Figure A21: Differential impact at the baseline across the distribution of the regional firms' turnover rate



(a) Permanent Employment Prob. (b) Employment Prob.

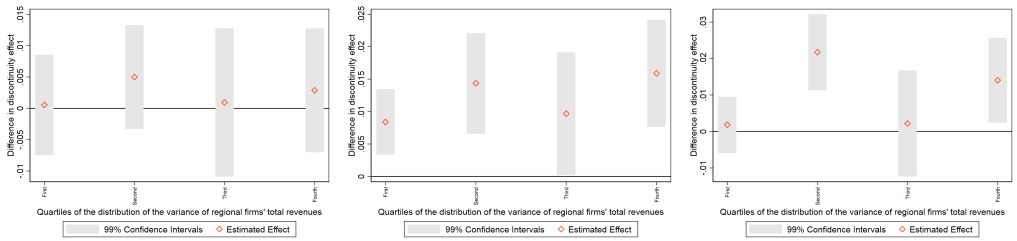
Figure A22: Differential gains after 30 months from the baseline across the distribution of the regional firms' turnover rate

A2 Variance of total revenues

Apprenticeships, rather than other labour contracts, serve as a stepping stone into permanent employment if its human capital component translates into an increase in productivity shared between the firm (higher rents) and the workers (higher future earnings). These shared future returns are conditional to a higher probability of working on a permanent basis in the firm that provided the training. From the employee perspective there are some analogies with a contract that fix a performance related pay component of the (future) earnings. The costs of the vocational training and the general education provided by the contract and the lower initial wage could be compensated by higher future earnings only if the worker's productivity increases. A well-known result of the literature is the negative relationship between uncertainty and performance related pay. The state of the regional market, an exogenous factor of production, and other sources of luck, cause the worker's output to vary even if she provides effort, (Lazear 1986). Consequently, individuals with the same level of ability and the same degree of risk aversion could find the apprenticeship labour contract less appealing in regions where uncertainty is high. I use AIDA data to calculate the variance (averaged out across time) of the distribution of non-missing total revenues of firms within a region.[1] Total revenues are normalised by the number of firms in the region. I then calculate the quartiles of the distribution of such regional variances and estimate whether the static ITT impact differs across these quartiles. Figure A23 shows that there is not a monotonic relationship between the static estimates of the difference in discontinuity effects and the quartiles of the distribution of variance. This finding is indicating that there could another possible interpretation of the role of a high regional variance of the distribution of firms' total revenues in a region. In fact, a higher variance could also signal the presence of high productive firms, (Lazear 2000). If high uncertainty (high variance) could be detrimental to a human capital investment, a low heterogeneity (low variance) in total revenues could be detrimental as well, if associated to low firms' productivity. The combination of these two counteracting mechanisms could generate the non-monotonic relationship observed in the data. Although the difference in discontinuity impacts on the apprenticeship rates are always precisely estimated and statistically different from zero, these effects are higher at the second and fourth quartiles of the variance distribution. This non-monotonic relationship maps into the effects on permanent employment that are statistically different from zero at the second and fourth quartiles of the variance distribution only.[2] All in all, this evidence suggests that uncertainty could play a role but the screening-sorting processes that let the apprenticeship labour contract be the main port of entry into permanent employment is related to a context where firms' productivity (i.e. firms with long-term expected production opportunities) is not low. Although these long-term expected production opportunities might be considered as a necessary condition, they could not be sufficient to completely explain the regional differences in the dynamic difference in discontinuity impacts.

[1] Firms' productivity could be proxied by the firm's per worker value added. However, the number of firms with a non-missing record shrinks too much when alternative measures to the firms' total revenues are used.

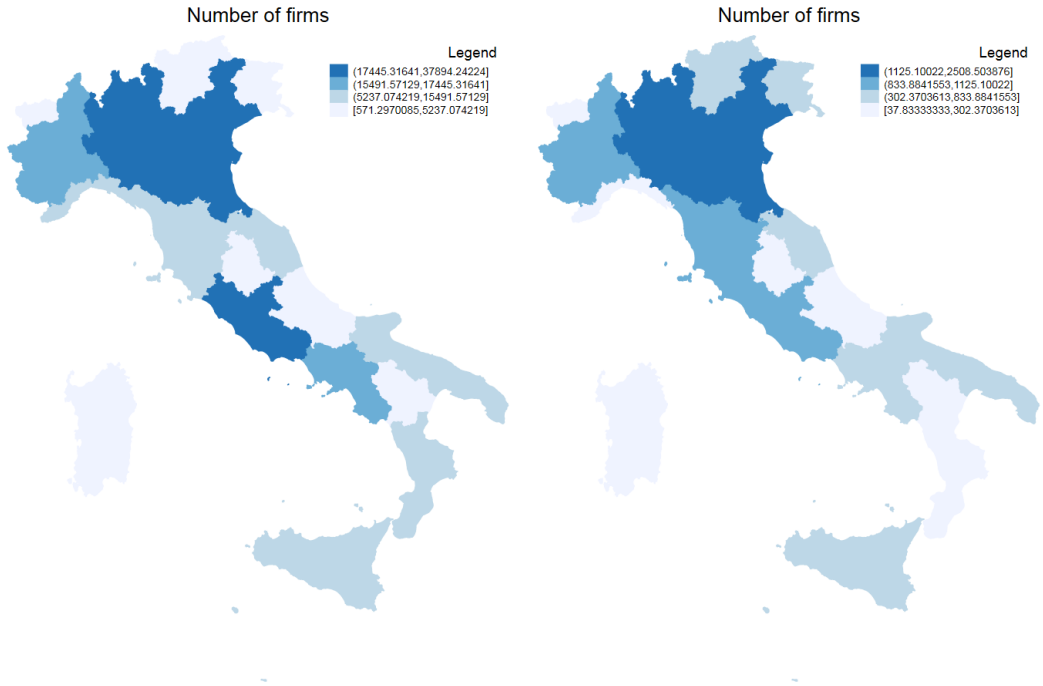
[2] The effect on permanent employment at the fourth quartile matches the impact on the apprenticeship probability. It is instead higher at the second quartile. The latter is the only quartile where a positive impact on the employment probability could be observed albeit it is imprecisely estimated since it is statistically different from zero at 0.12 significance level.



(a) Employment Prob. (b) Apprenticeship Prob. (c) Permanent employment Prob.

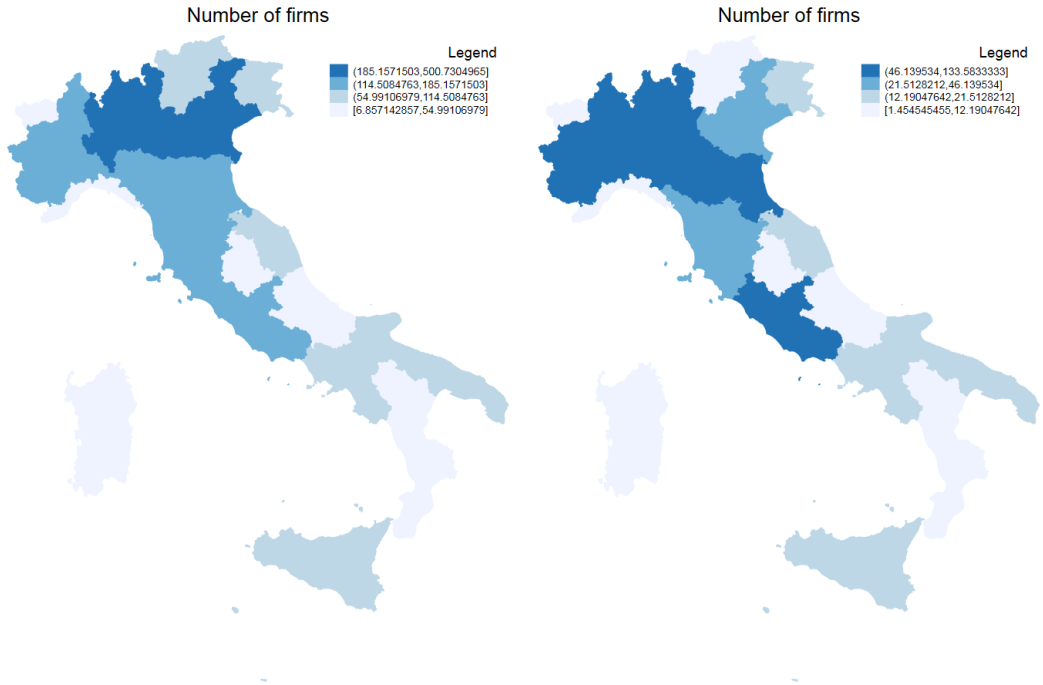
Figure A23: Difference in discontinuity: differential impact across variance of the regional firms' total revenues

A3 Regional sectoral and firm size composition



(a) Size: 0 to 9 workers.

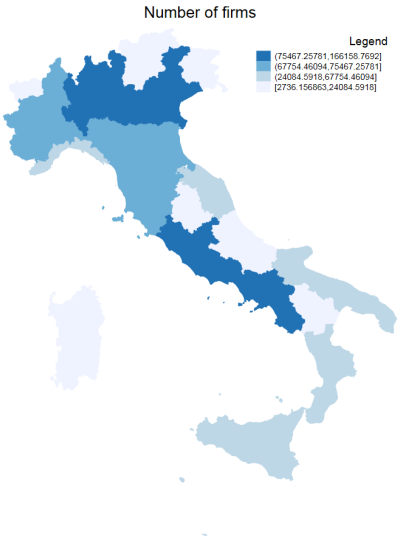
(b) Size: 10 to 49 workers.



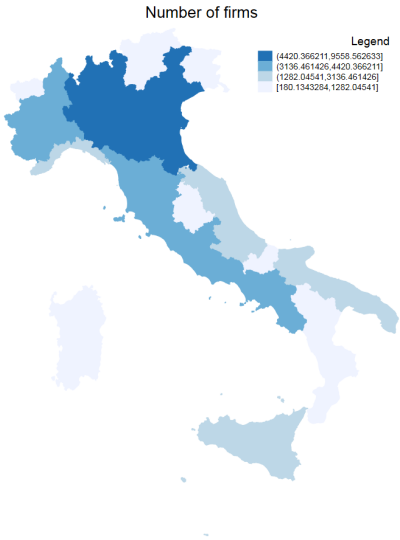
(c) Size: 50 to 249 workers.

(d) Size: more than 249 workers.

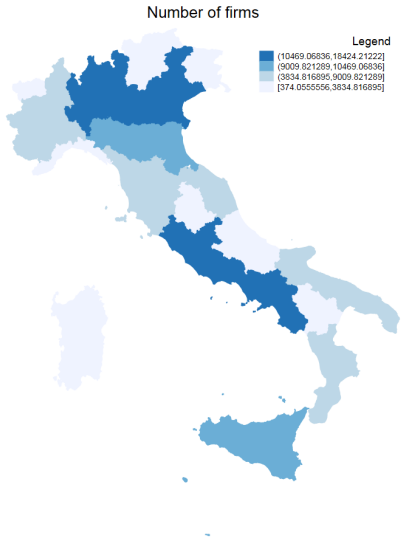
Figure A24: Geographical variations in number of firms by firm class size



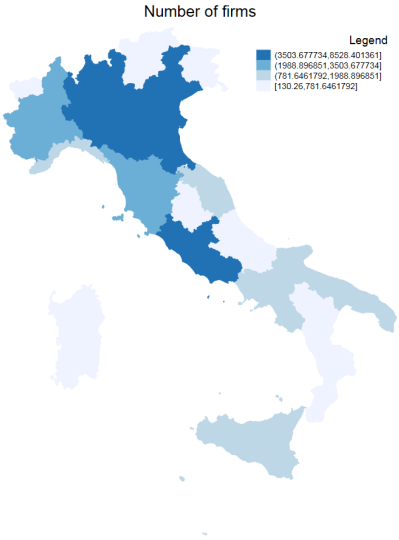
(a) Agriculture.



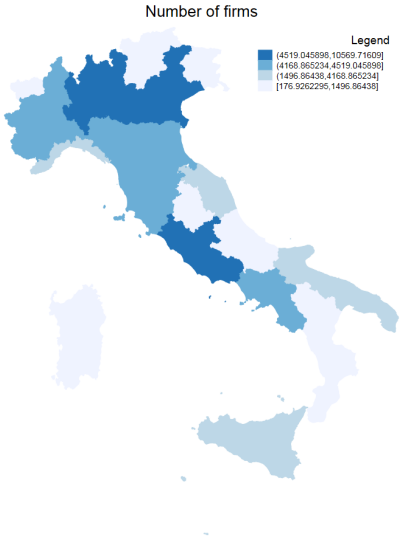
(b) Industry.



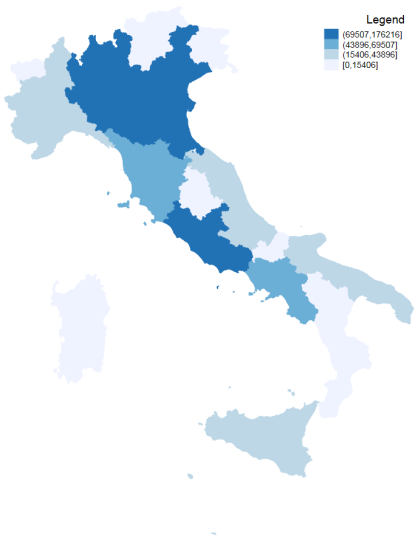
(c) Retail trade, transportations and accommodation.



(d) Comunications, Financial and real estate.

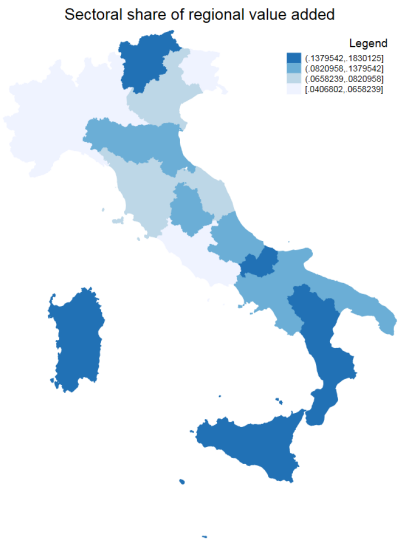


(e) Other services.

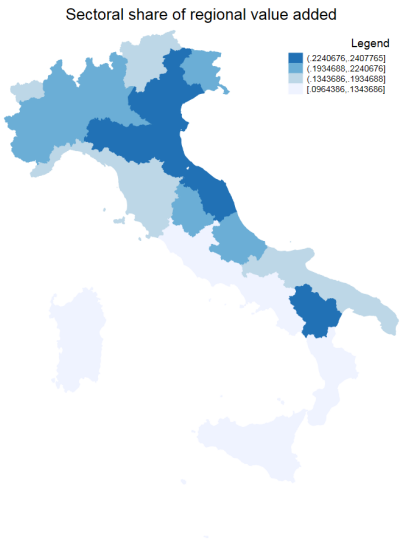


(f) Total number of active firms in a region.

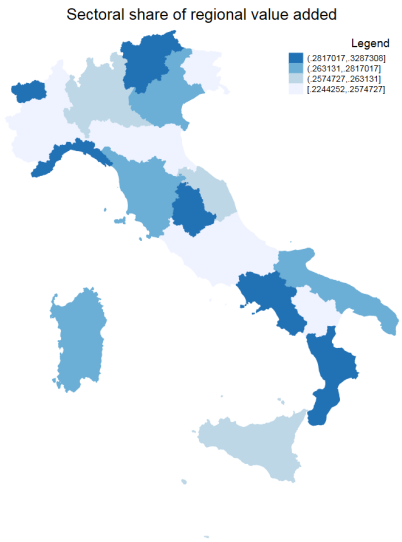
Figure A25: Geographical variations in number of firms by sectors



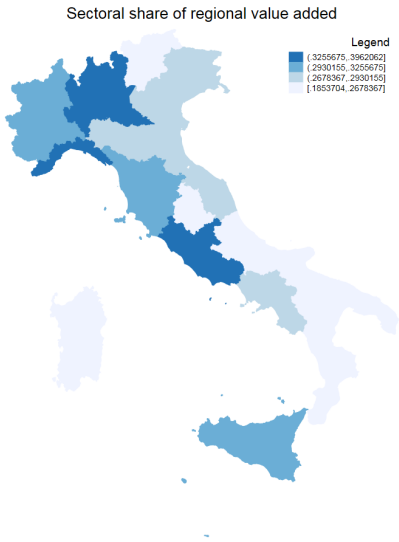
(a) Agriculture.



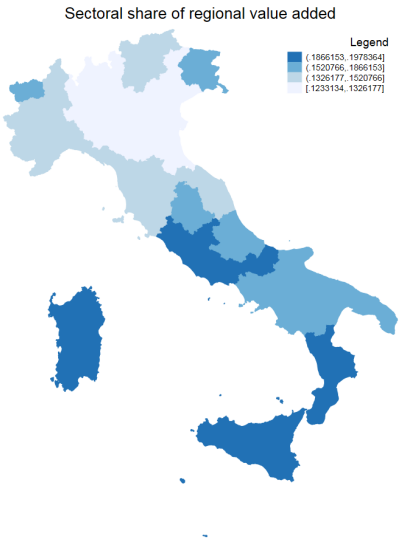
(b) Industry.



(c) Retail trade, transportations and accommodation.



(d) Comunications, Financial and real estate.

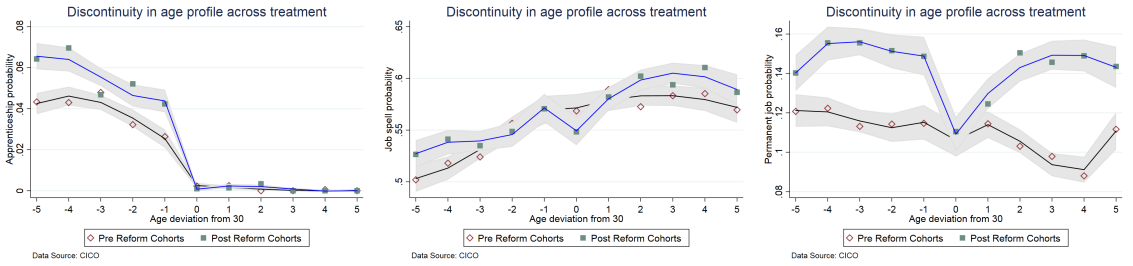


(e) Other services.

Figure A26: Geographical variations in sectoral share of regional value added

B1 Graphical analysis region by region

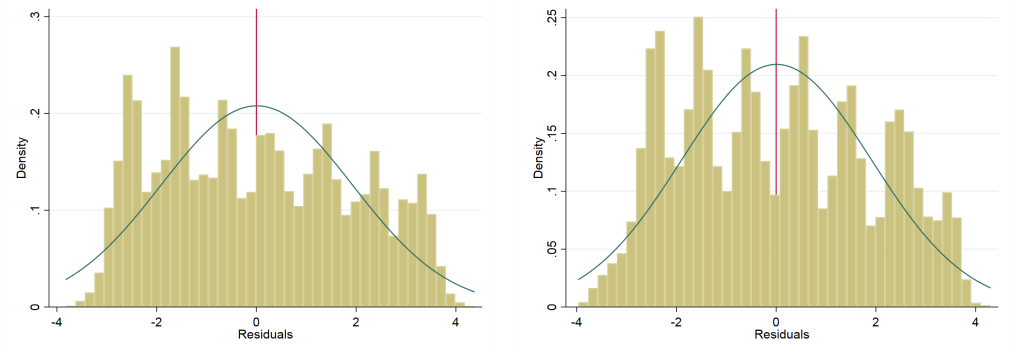
B1.1 Abruzzo



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

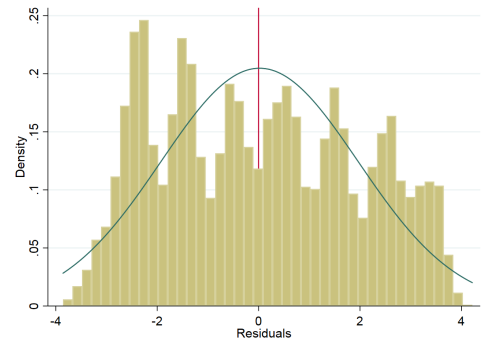
Figure B1: Difference in discontinuity for those born in Abruzzo

Figure B2: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

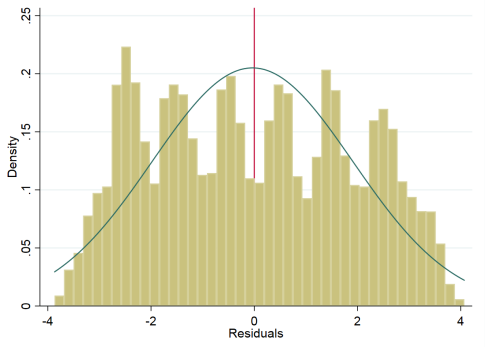


(a) First quartile

(b) Second quartile



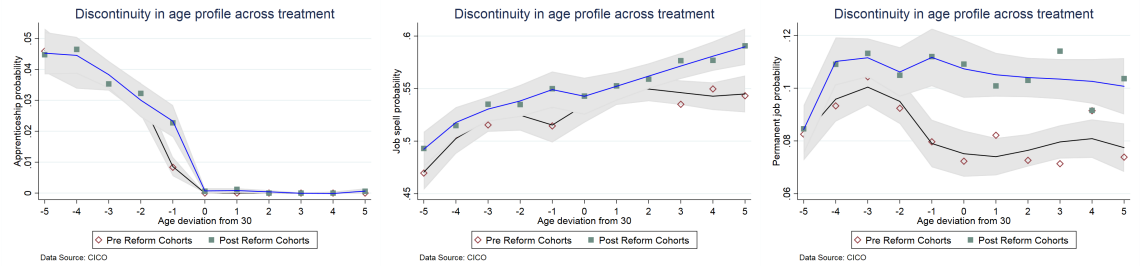
(c) Third quartile



(d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

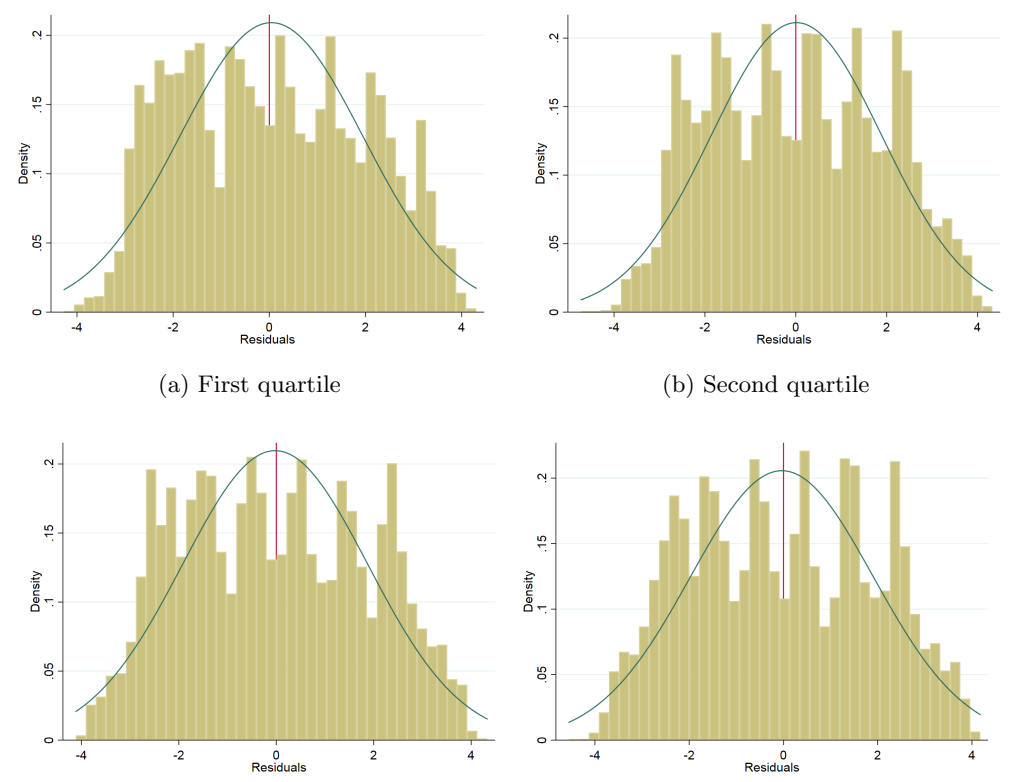
B1.2 Basilicata



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B3: Difference in discontinuity for those born in Basilicata

Figure B4: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

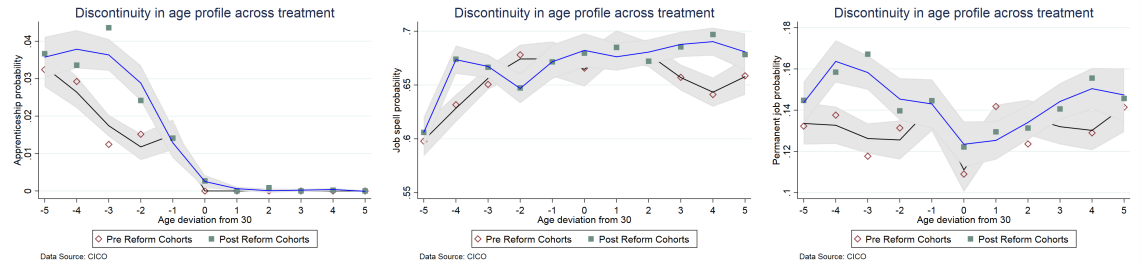


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

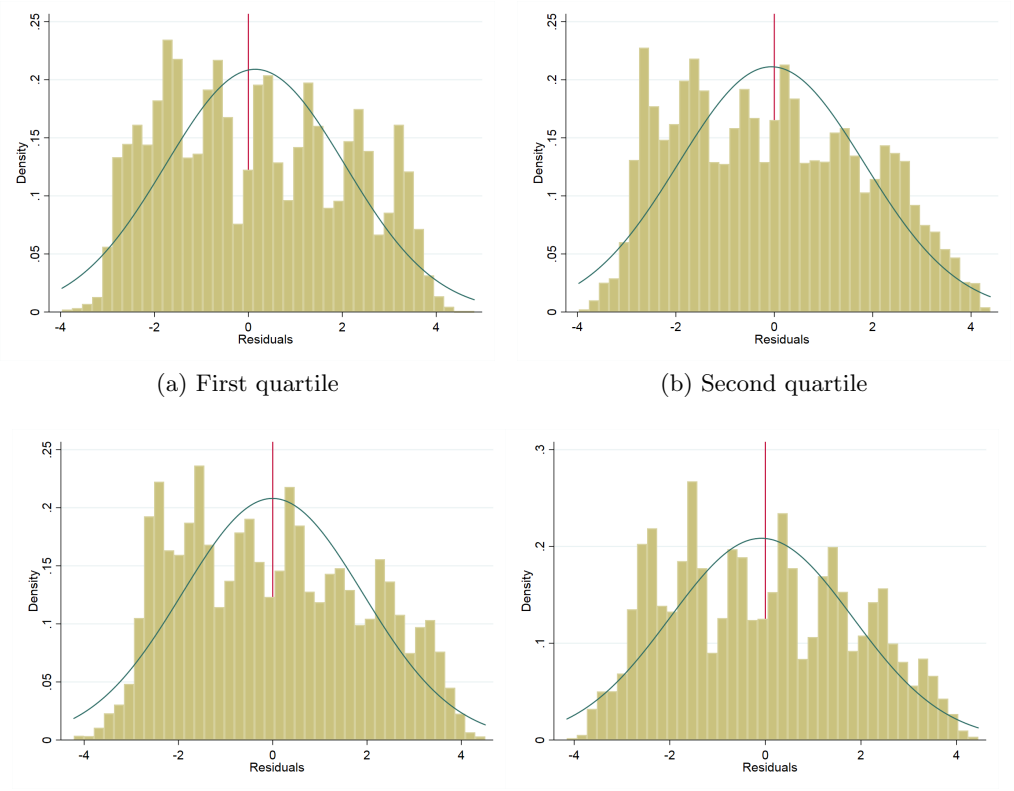
B1.3 Trentino Alto Adige



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B5: Difference in discontinuity for those born in Trentino Alto Adige.

Figure B6: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

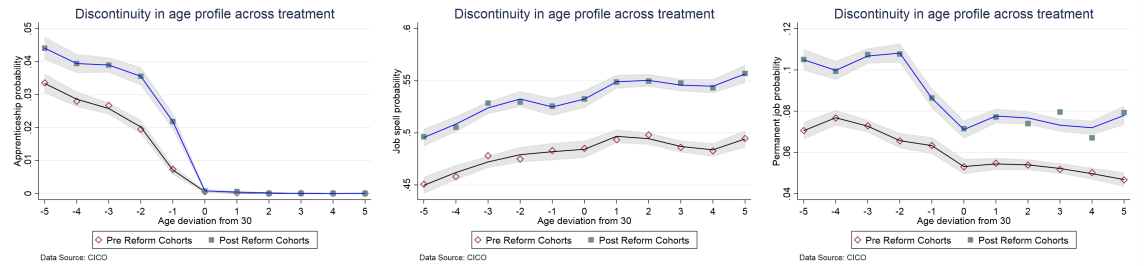


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

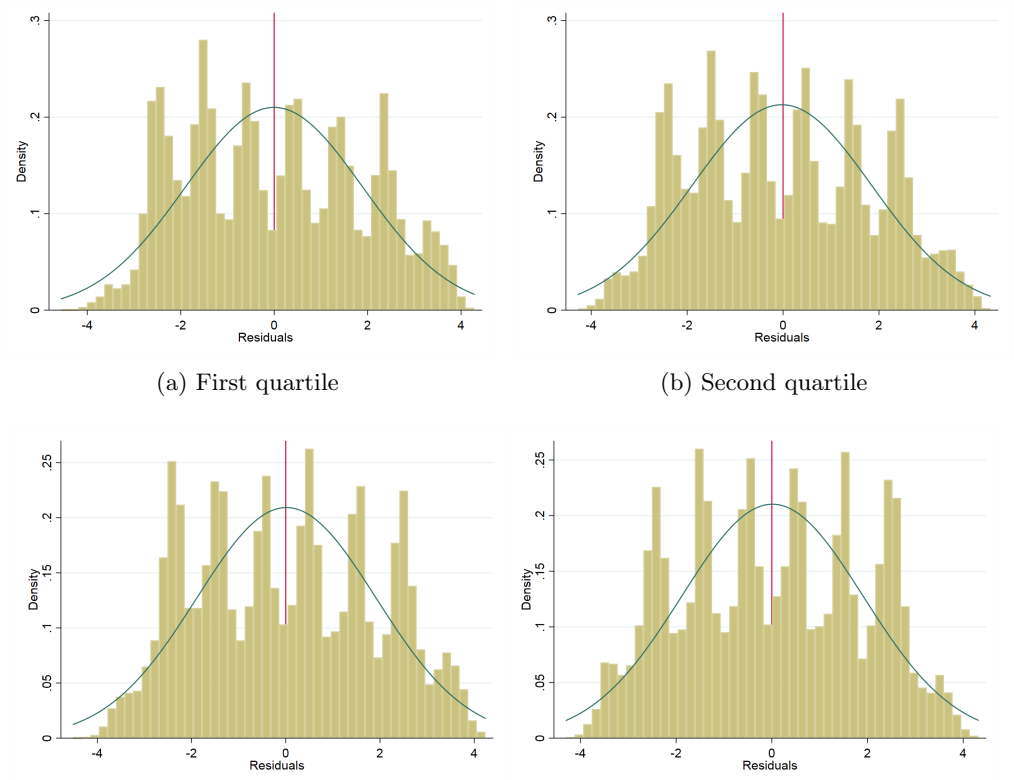
B1.4 Calabria



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B7: Difference in discontinuity for those born in Calabria.

Figure B8: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

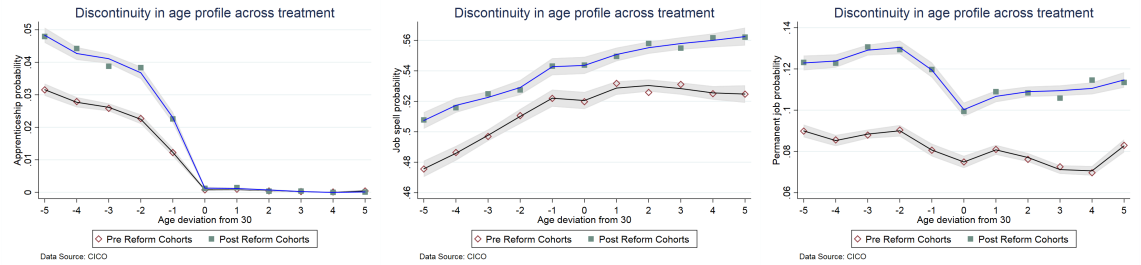


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

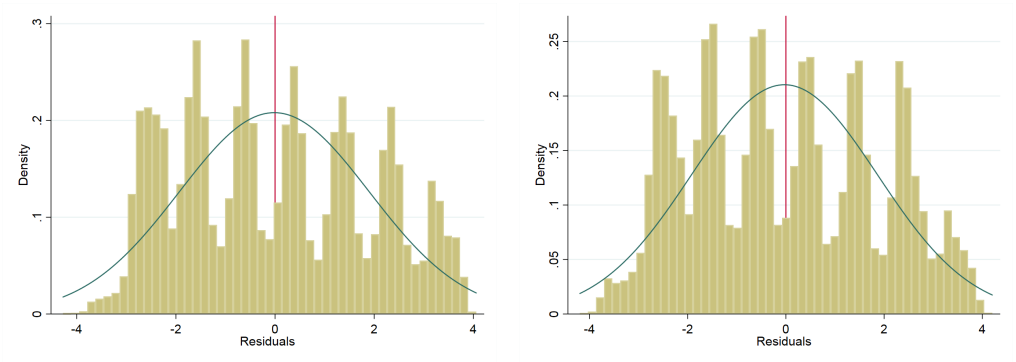
B1.5 Campania



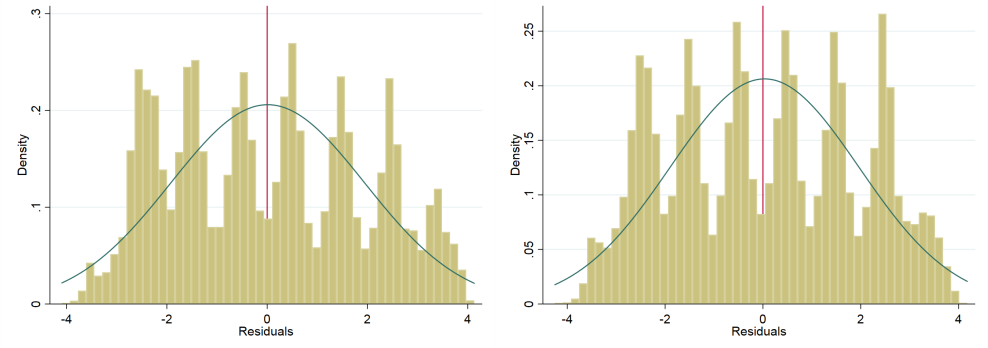
(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B9: Difference in discontinuity for those born in Campania

Figure B10: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.



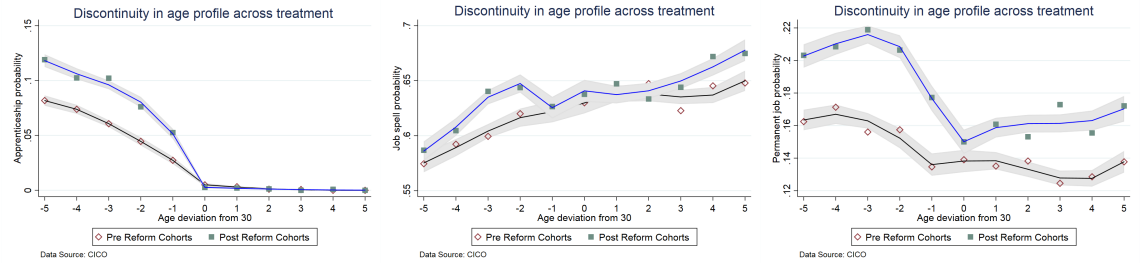
(a) First quartile (b) Second quartile



(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

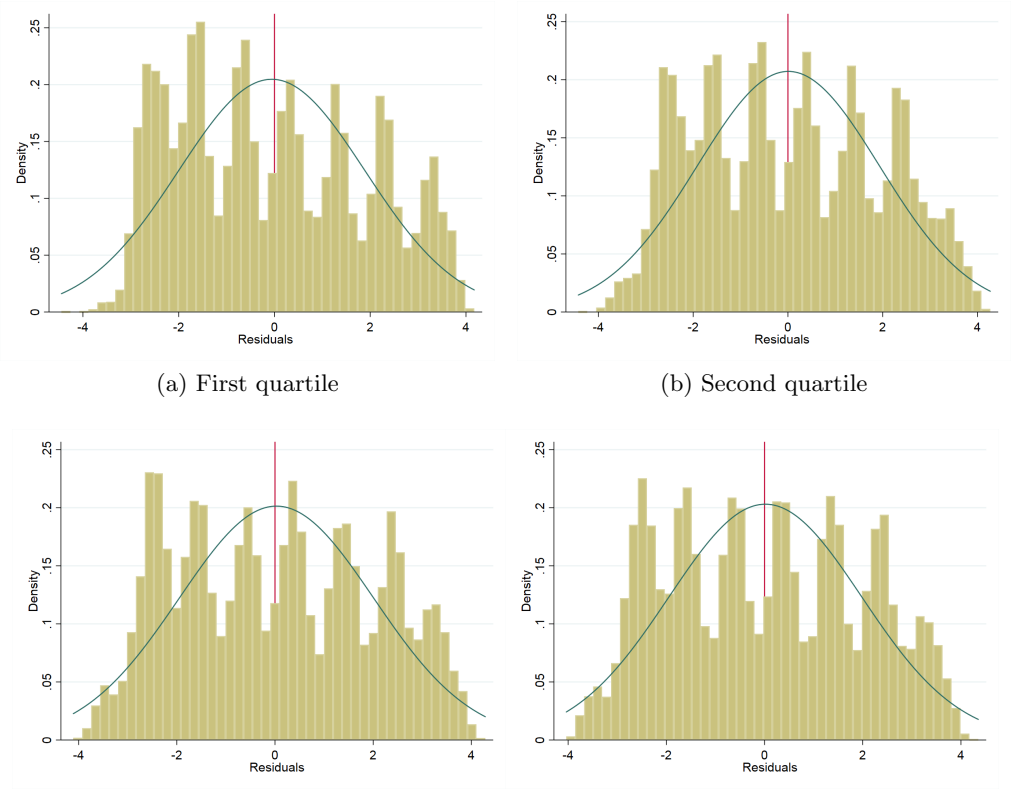
B1.6 Emilia Romagna



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B11: Difference in discontinuity for those born in Emilia Romagna

Figure B12: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

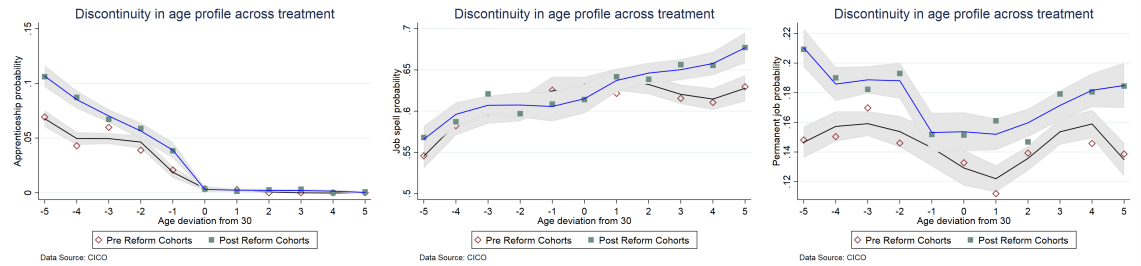


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

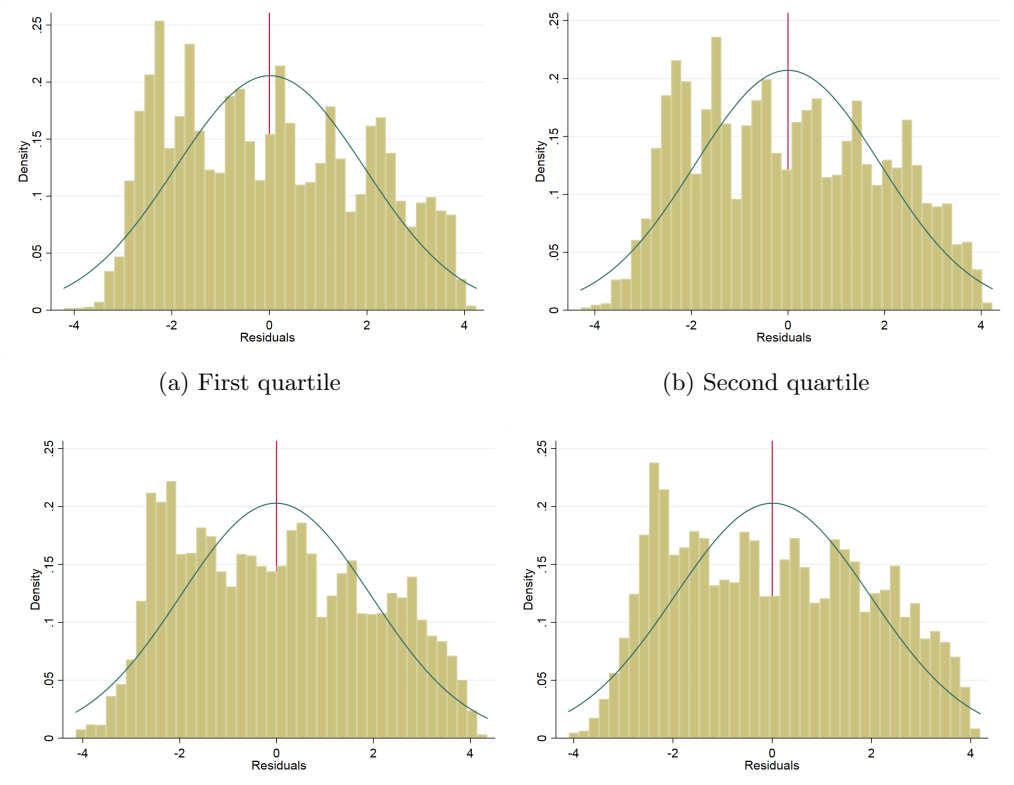
B1.7 Friuli Venezia Giulia



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B13: Difference in discontinuity for those born in Friuli Venezia Giulia.

Figure B14: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

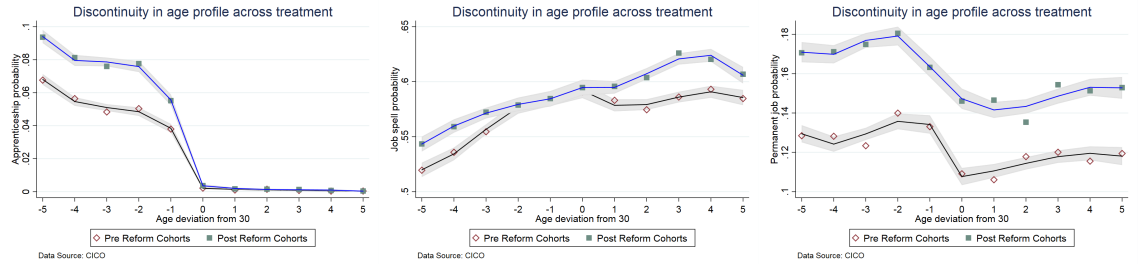


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

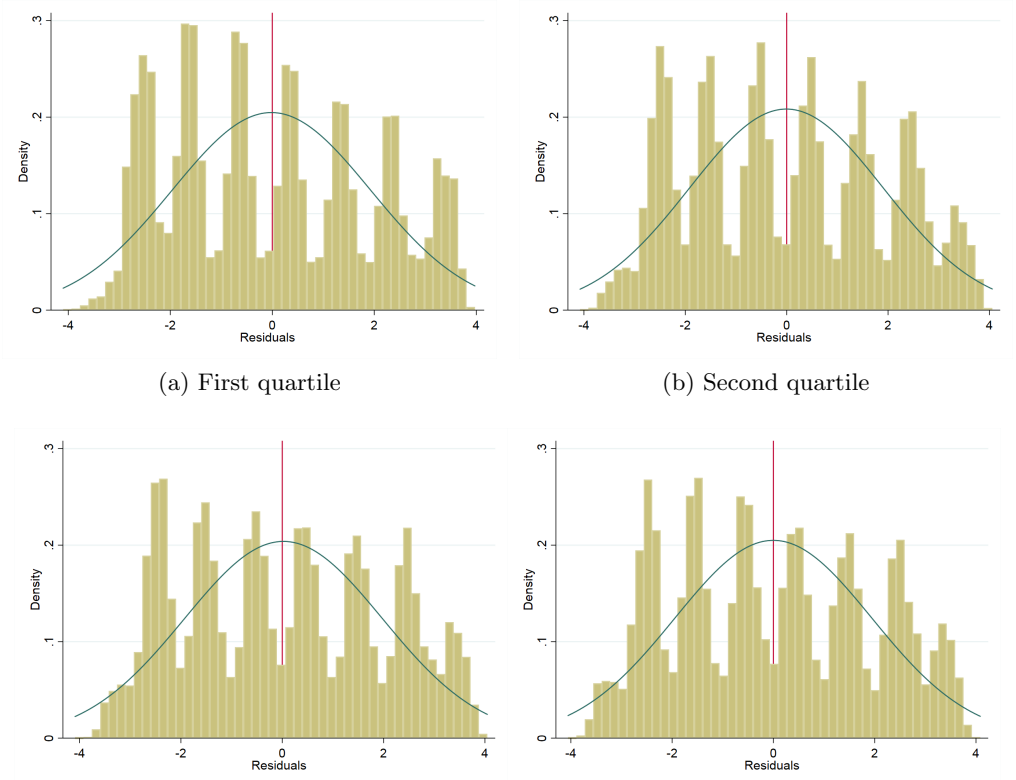
B1.8 Lazio



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B15: Difference in discontinuity for those born in Lazio.

Figure B16: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

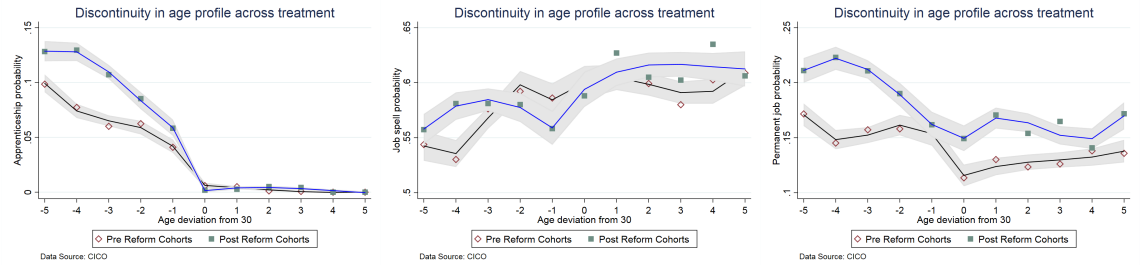


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

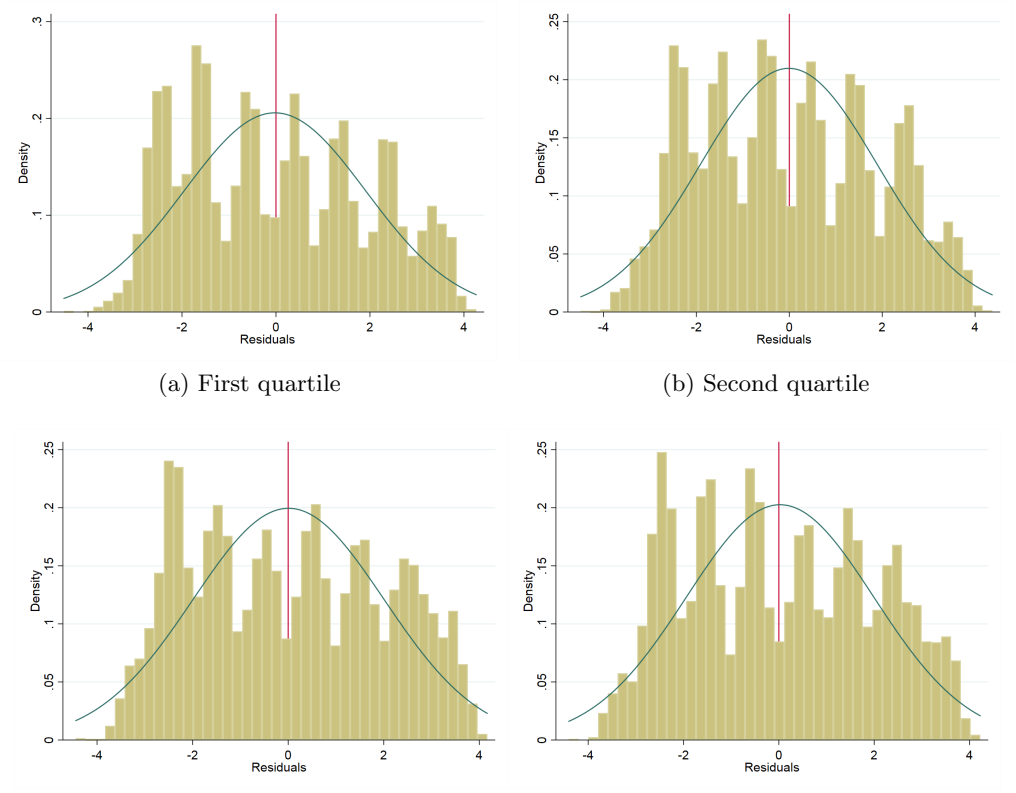
B1.9 Liguria



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B17: Difference in discontinuity for those born in Liguria.

Figure B18: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

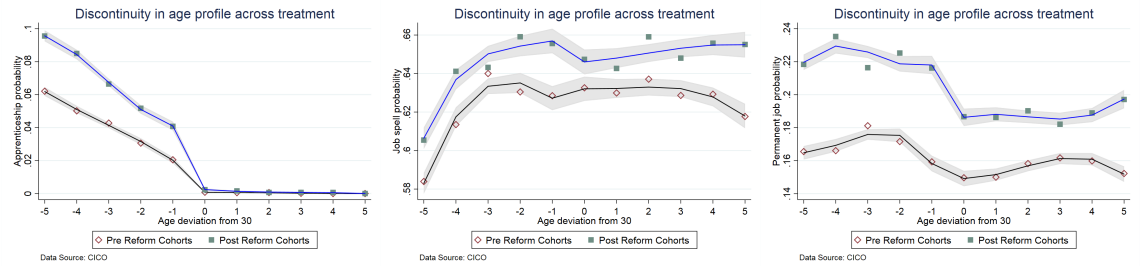


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

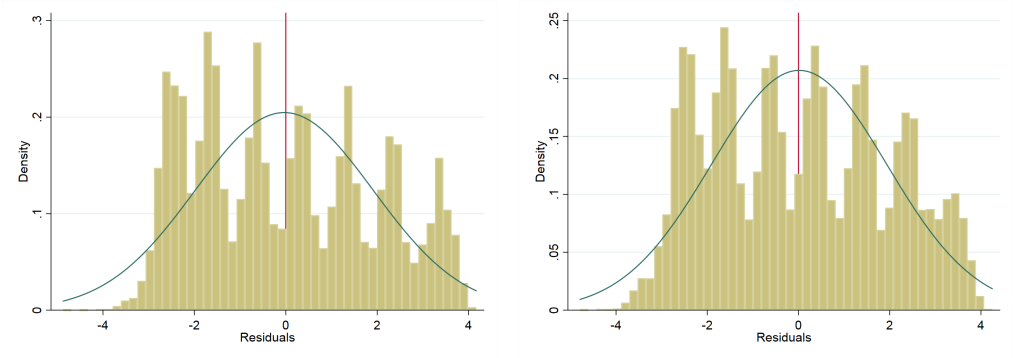
B1.10 Lombardia



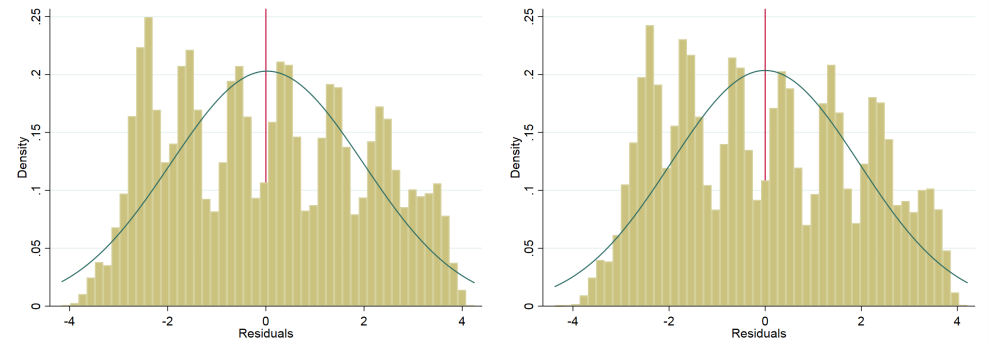
(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B19: Difference in discontinuity for those born in Lombardia.

Figure B20: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.



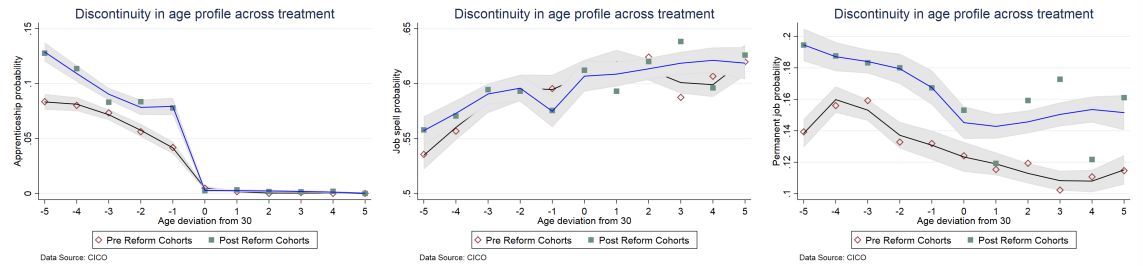
(a) First quartile (b) Second quartile



(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

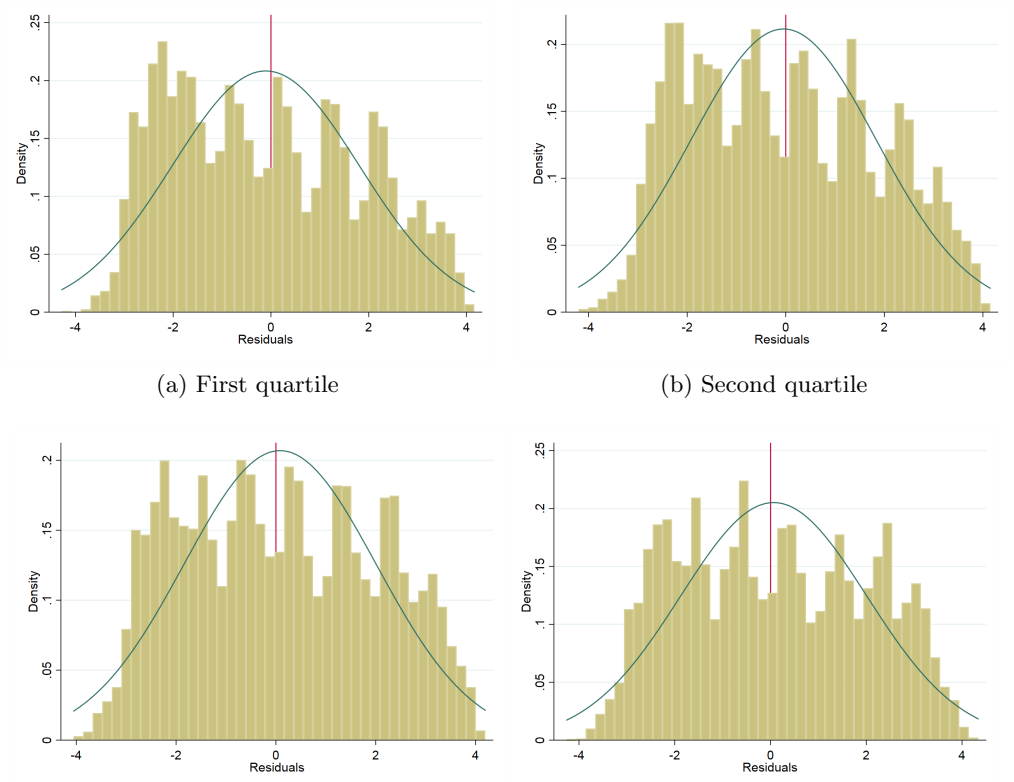
B1.11 Marche



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B21: Difference in discontinuity for those born in Marche.

Figure B22: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

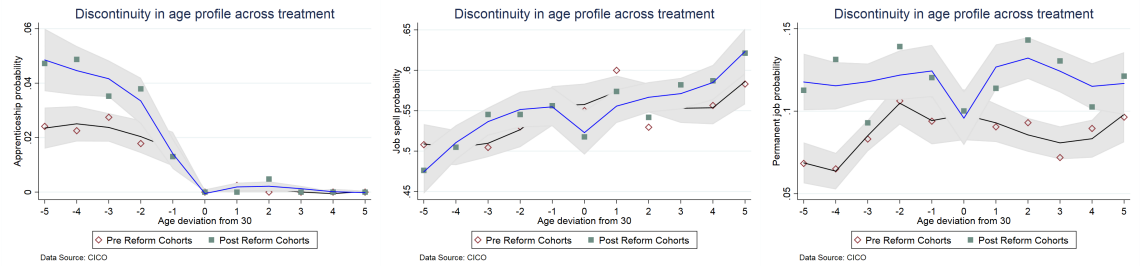


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

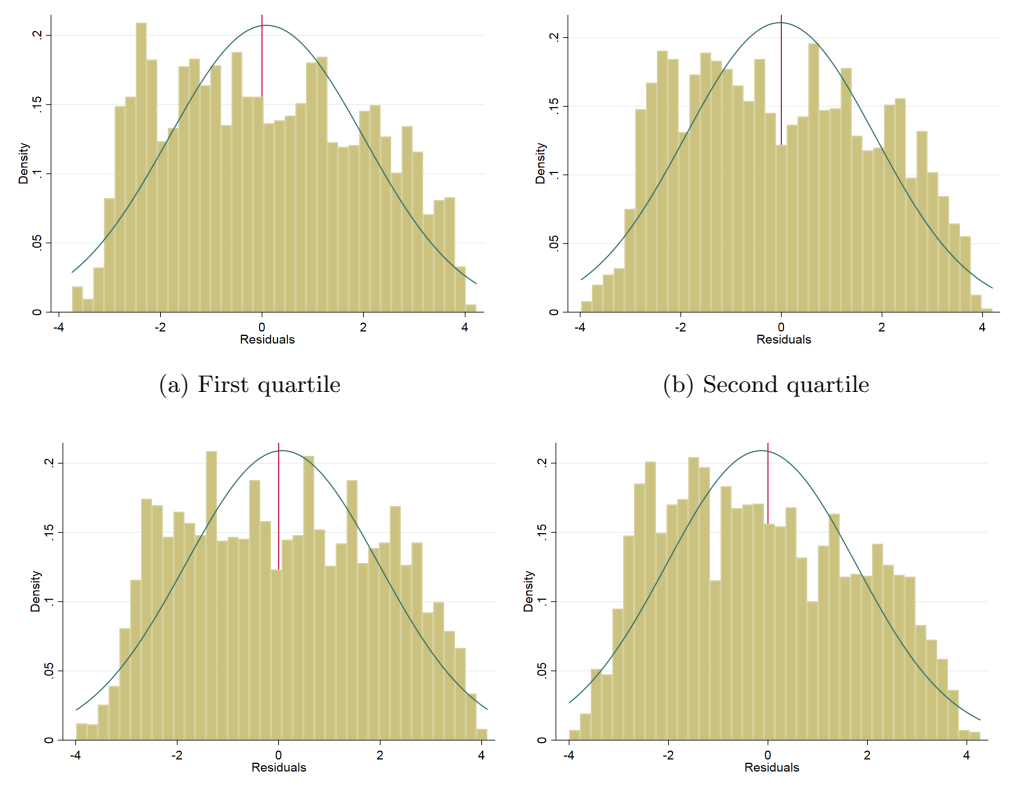
B1.12 Molise



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B23: Difference in discontinuity for those born in Molise.

Figure B24: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

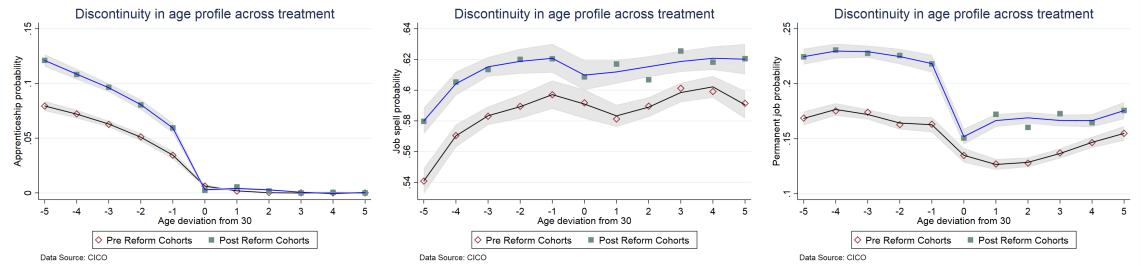


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

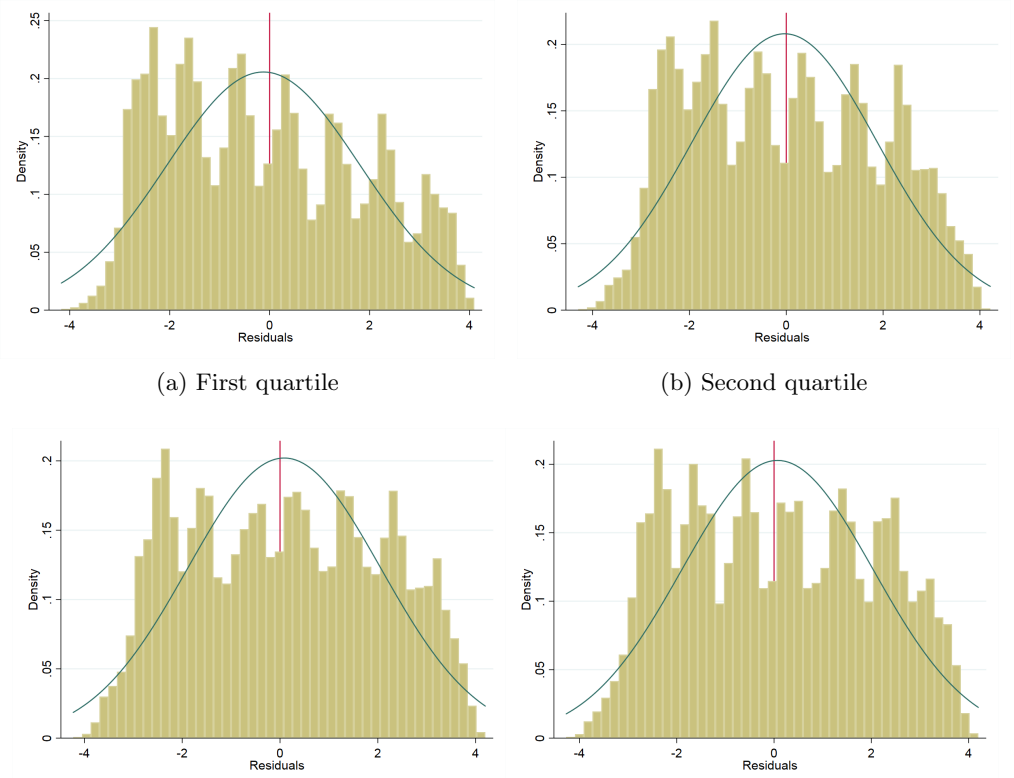
B1.13 Piemonte



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B25: Difference in discontinuity for those born in Piemonte.

Figure B26: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

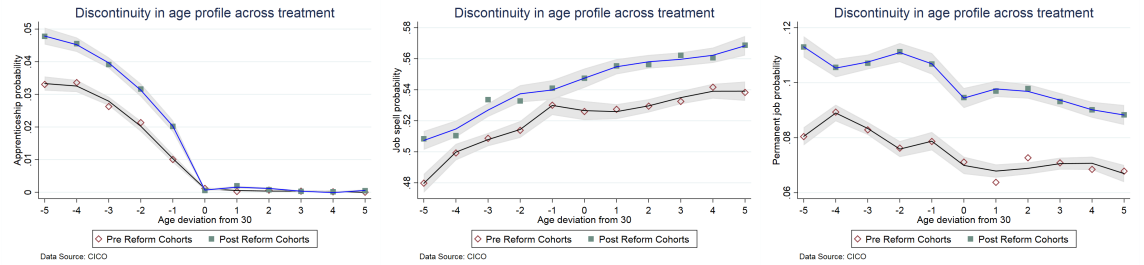


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

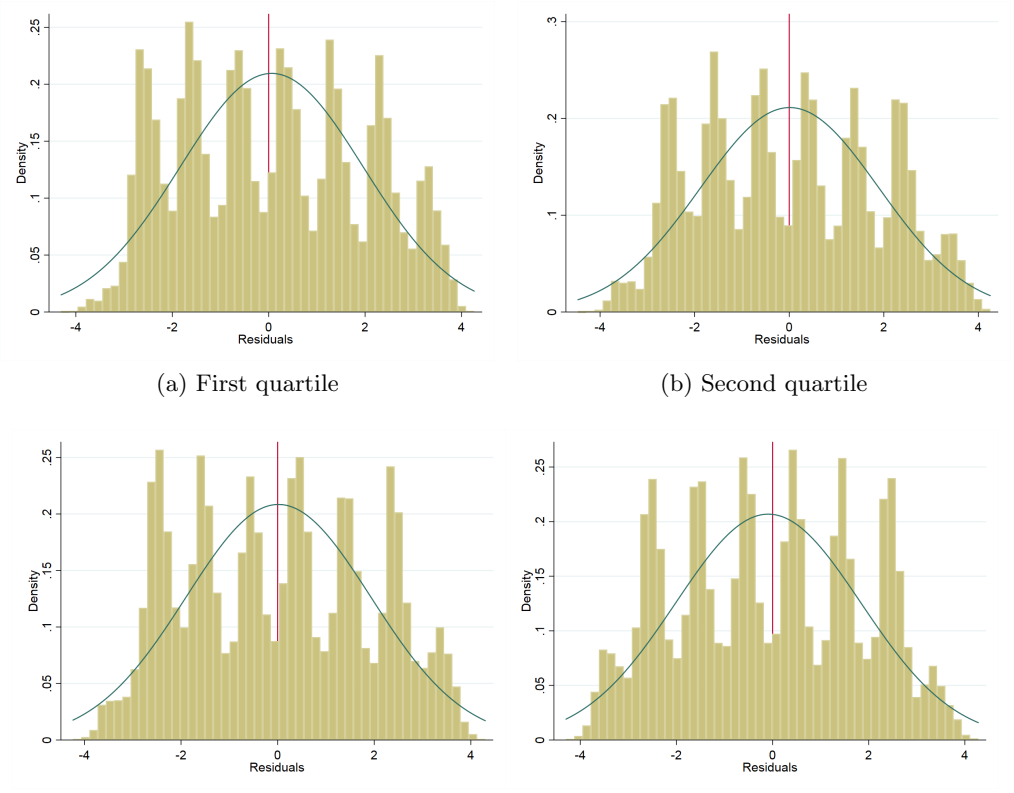
B1.14 Puglia



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B27: Difference in discontinuity for those born in Puglia.

Figure B28: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

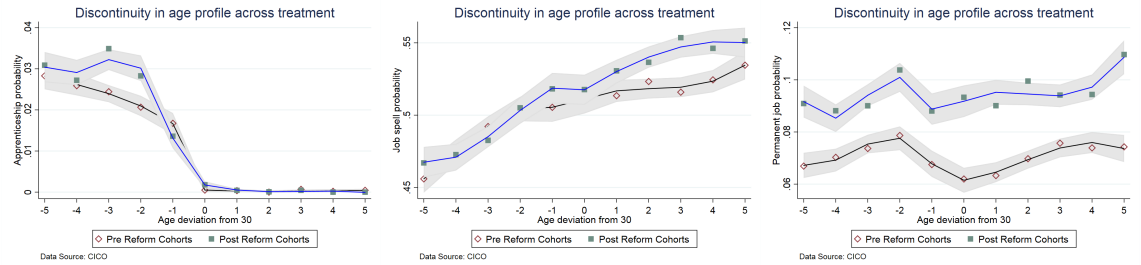


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

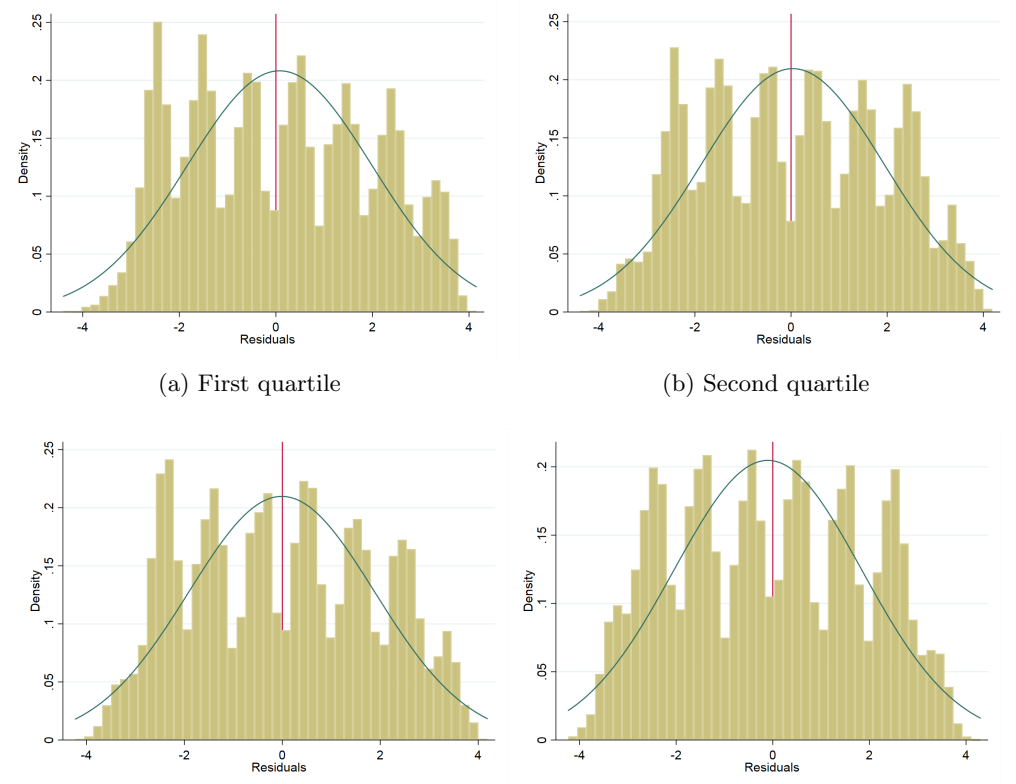
B1.15 Sardegna



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B29: Difference in discontinuity for those born in Sardegna.

Figure B30: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

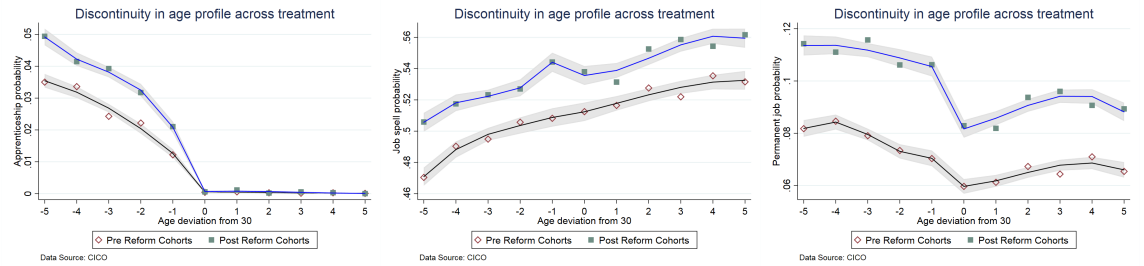


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

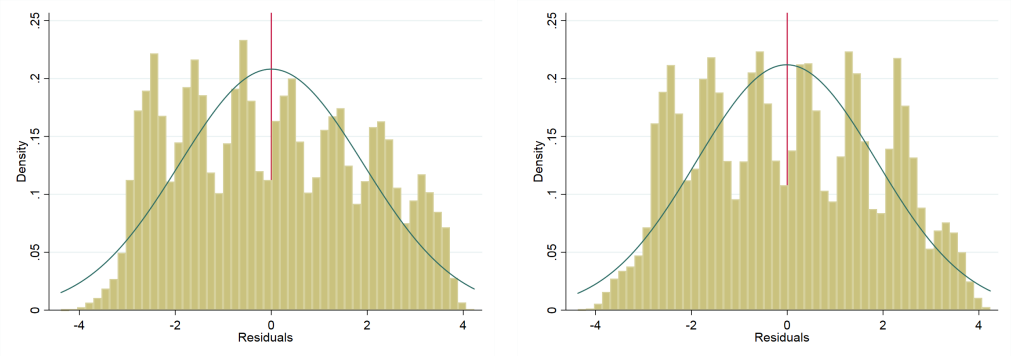
B1.16 Sicilia



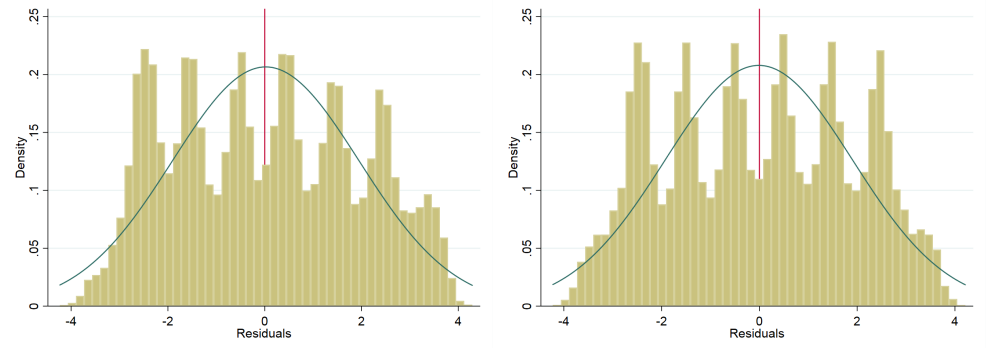
(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B31: Difference in discontinuity for those born in Sicilia.

Figure B32: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.



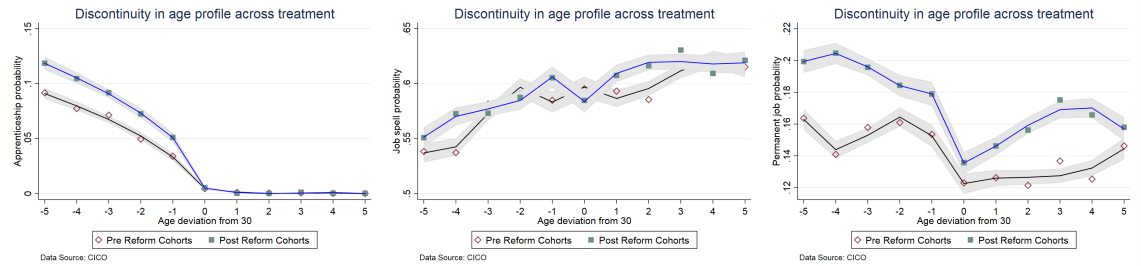
(a) First quartile (b) Second quartile



(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

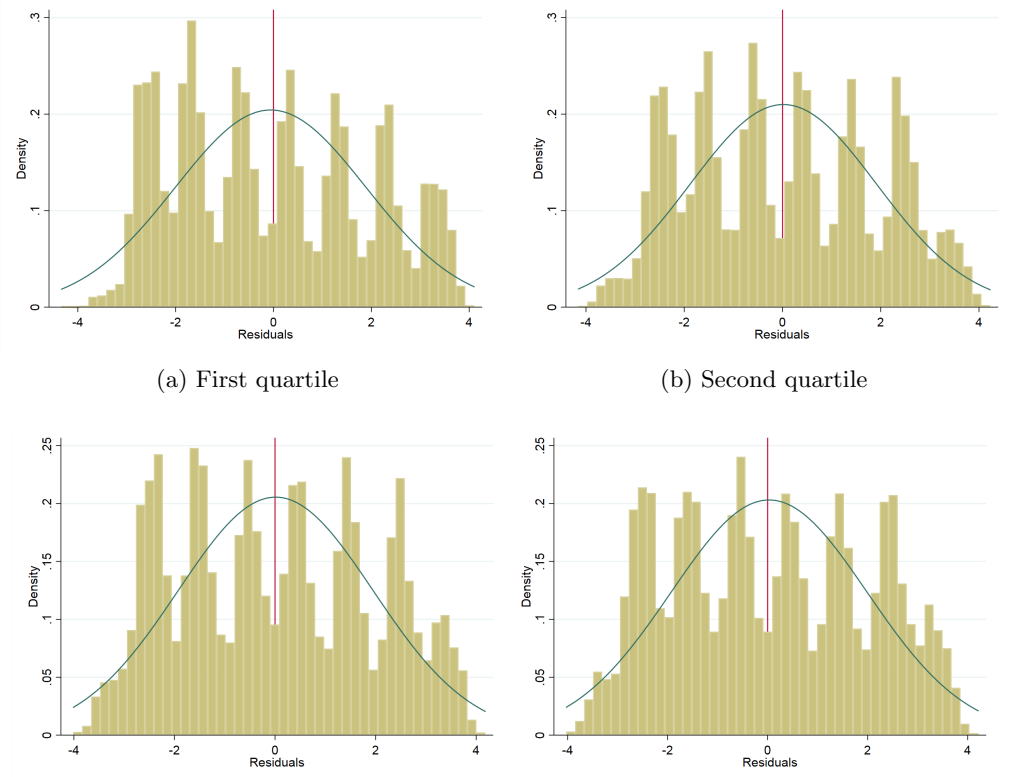
B1.17 Toscana



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B33: Difference in discontinuity for those born in Toscana.

Figure B34: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

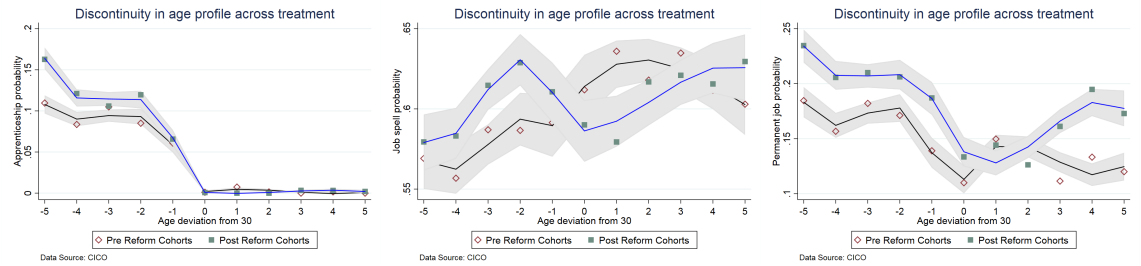


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

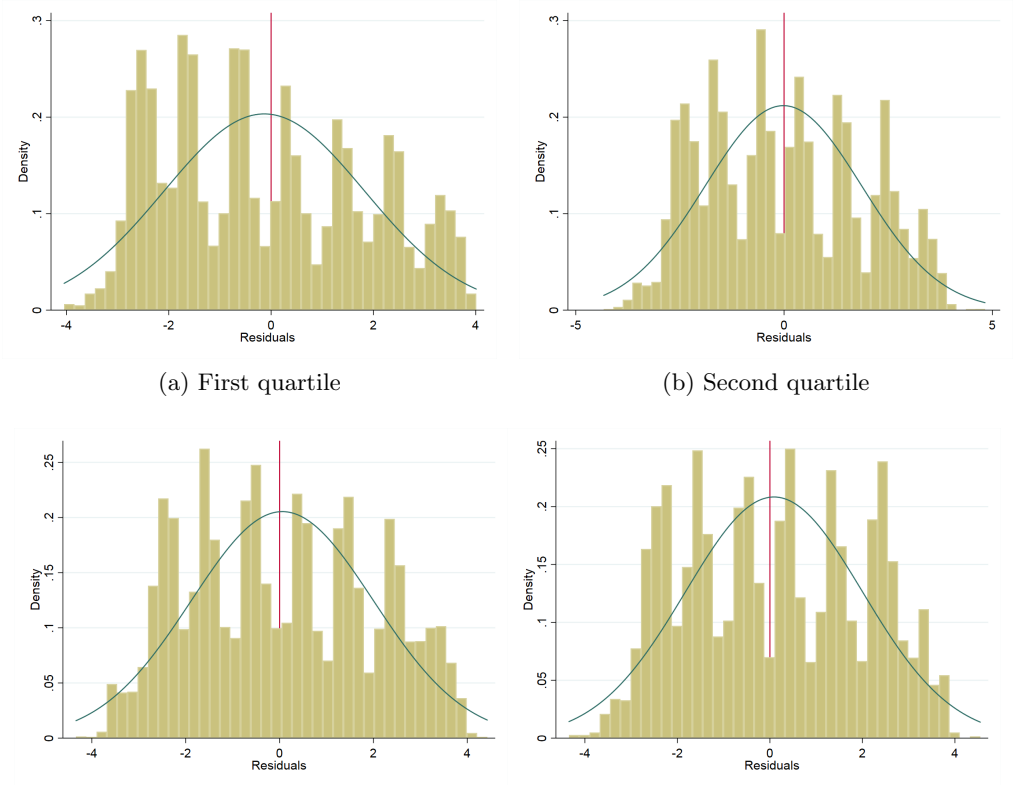
B1.18 Umbria



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B35: Difference in discontinuity for those born in Umbria.

Figure B36: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

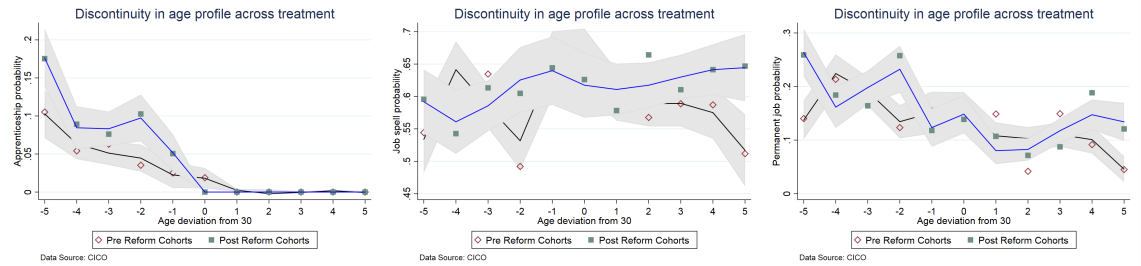


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

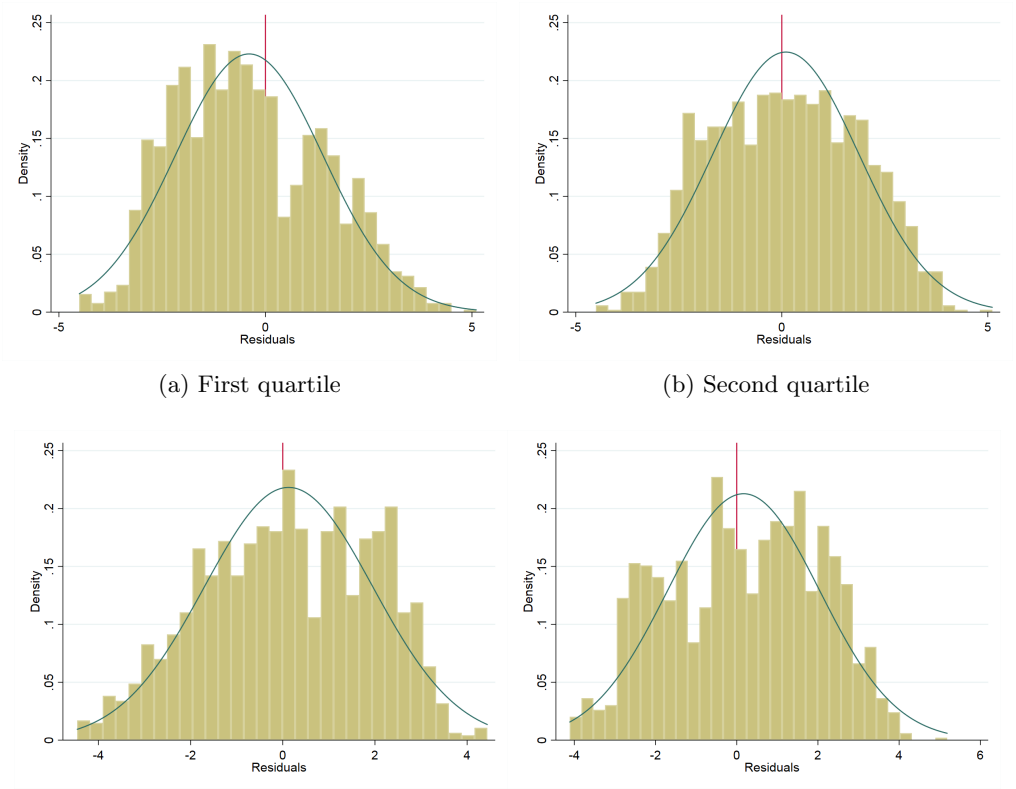
B1.19 Valle d'Aosta



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B37: Difference in discontinuity for those born in Valle d'Aosta.

Figure B38: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

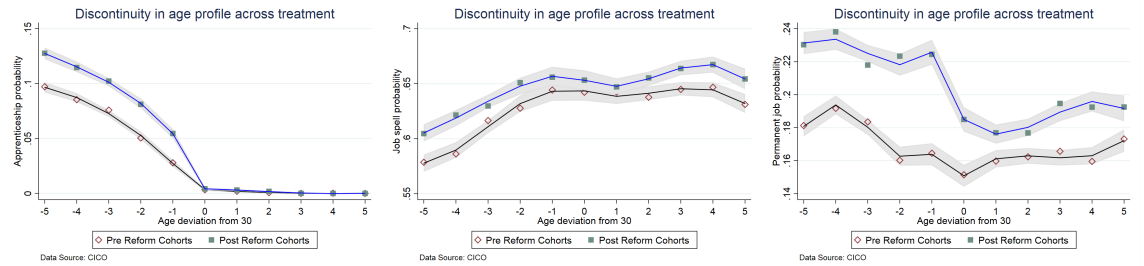


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

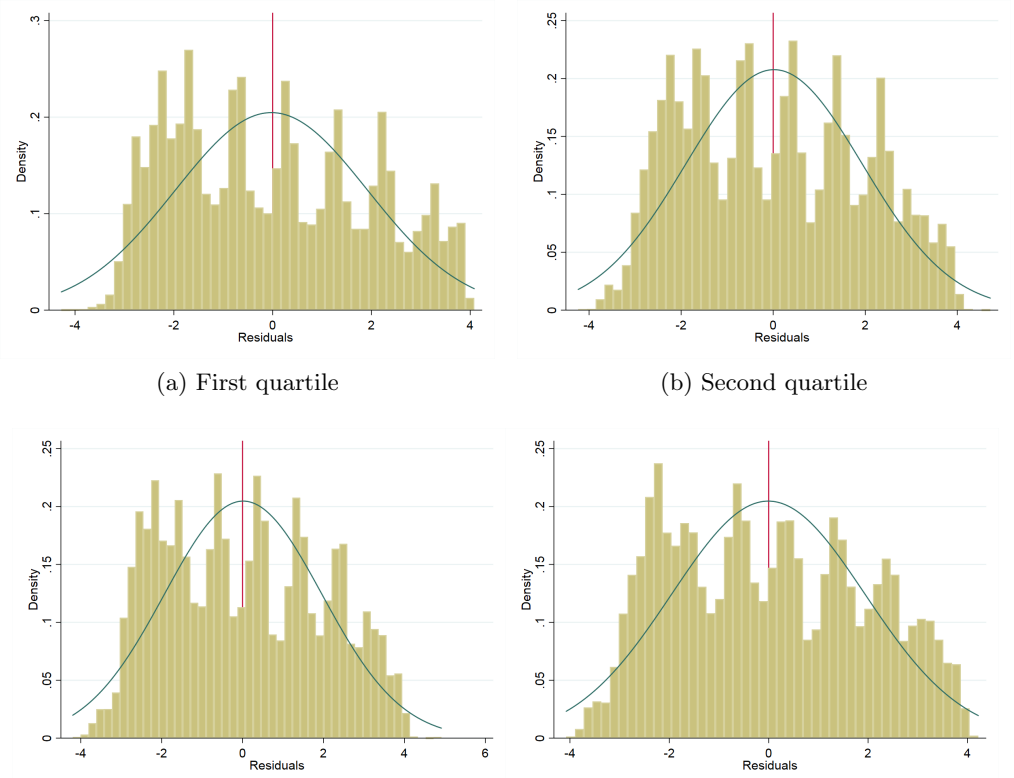
B1.20 Veneto



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B39: Difference in discontinuity for those born in Veneto.

Figure B40: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.

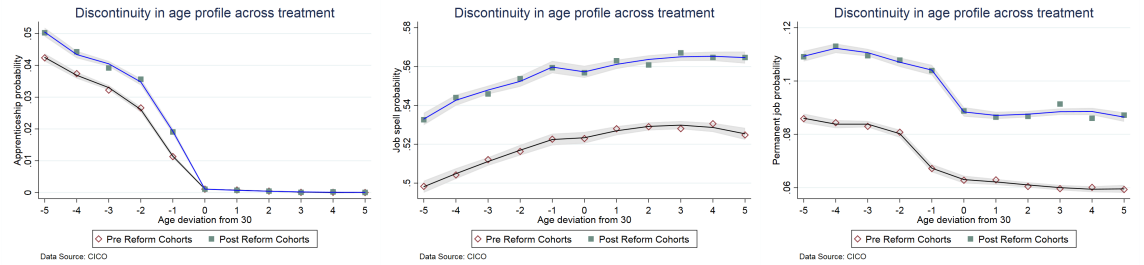


(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

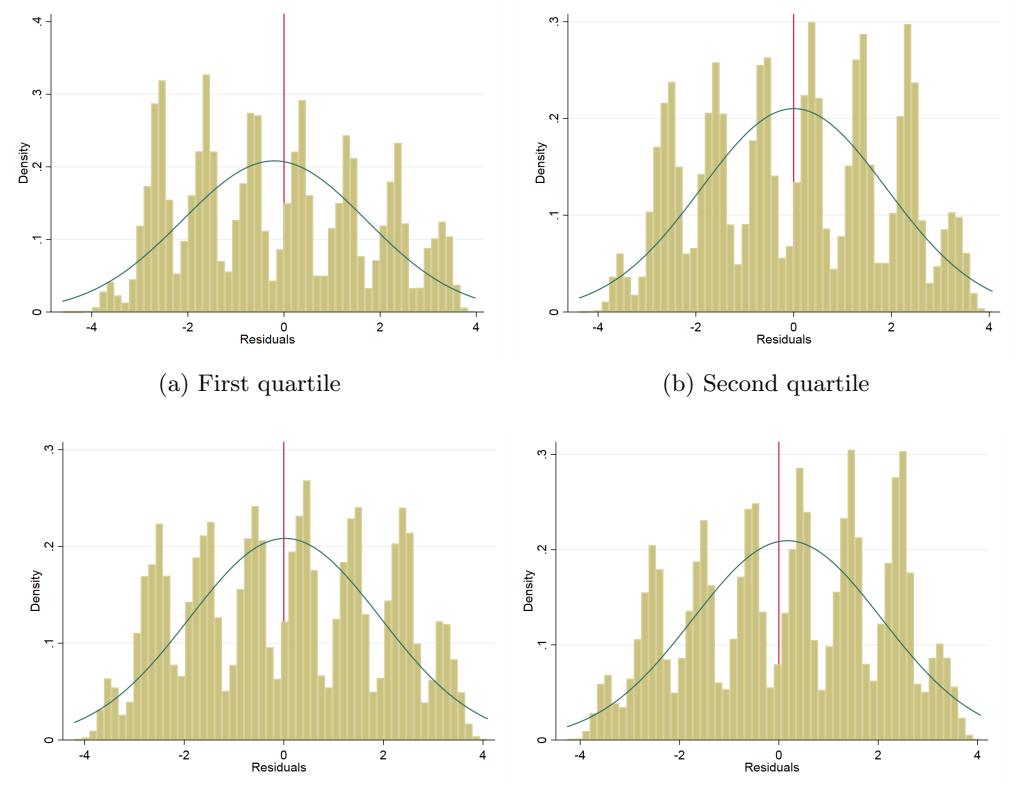
B1.21 Foreign citizenship



(a) Apprenticeship Probability. (b) Employment Probability. (c) Permanent Employment Probability.

Figure B41: Difference in discontinuity for those with a foreign citizenship.

Figure B42: Density of the residuals of age conditional on observable characteristics and quartile of the distributions of residuals of equation (1) where permanent employment probability is the outcome variable.



(a) First quartile (b) Second quartile

(c) Third quartile (d) Fourth quartile

Notes: Density of the residuals V of the forcing variables (age a) regression conditional on observable characteristics X (grouped by gender, region of birth, sector of activity and level of education) and on the quartiles of the distribution of the residuals U of equation 1 augmented by covariates.

References

Lazear, E. (1986). Salaries and piece rates, *The Journal of Business* **59**(3): 405–31.

Lazear, E. (2000). Performance pay and productivity, *American Economic Review* **90**(5): 1346–1361.

Ultimi Contributi di Ricerca CRENoS

I Paper sono disponibili in: http://www.crenos.unica.it

19/15 *Daniela Sonedda,* "Regional disparities in the functioning of the labour markets"

19/14 *Bianca Biagi, Barbara Dettori, Raffaele Paci, Stefano Usai,* "Economic development in Sardinia: overcoming the insularity gap"

19/13 *Miguel Casares, Luca Deidda, Jose E. Galdon-Sanchez,* "On financial frictions and firm market power"

19/12 *Massimiliano Bratti, Maurizio Conti, Giovanni Sulis,* "Employment Protection and Firm-provided Training: Quasi-experimental Evidence from a Labour Market Reform"

19/11 *Jessica Goldberg, Mario Macis, Pradeep Chintagunta*, "Incentivized Peer Referrals for Tuberculosis Screening: Evidence from India"

19/10 *Julio J. Elías, Nicola Lacetera, Mario Macis,* "Paying for Kidneys? A Randomized Survey and Choice Experiment"

19/09 *Fabio Cerina, Elisa Dienesch, Alessio Moro, Michelle Rendall,* "Spatial Polarization"

19/08 *Michele Battisti, Massimo Del Gatto, Christopher F. Parmeter,* "Skill Biased Technical Change and Misallocation: a Unified Framework"

19/07 *Fabrizio Fusillo, Francesco Quatraro, Stefano Usai,* "Going Green: Environmental Regulation, eco-innovation and technological alliances"

19/06 *Oliviero A. Carboni, Giuseppe Medda,* "External R&D Acquisition and Product Innovation"

19/05 *José J. Cao-Alvira, Luca G. Deidda,* "Development of Bank Microcredit"

19/04 *Vania Licio,* "When history leaves a mark: a new measure of Roman roads"

19/03 *Simone Franceschini, Gerardo Marletto,* "Reorganization of supply chains as a key for the envision of socio- technical transitions. The case of tourism"

19/02 *Elias Carroni, Dimitri Paolini,* "The business model of a streaming platform"

19/01 *Stefania Capecchi, Marta Meleddu, Manuela Pulina, Giuliana Solinas,* "Mixture models for consumers' preferences in healthcare"

18/13 *Adelaide Baronchelli, Teodora Erika Uberti,* "Exports and FDI: Comparing Networks in the New Millennium"

18/12 *Gabriele Cardullo, Maurizio Conti, Giovanni Sulis,* "Unions, Two-Tier Bargaining and Physical Capital Investment: Theory and Firm-Level Evidence from Italy"

18/11 *Jing Guan, J.D. Tena,* "Estimating the Effect of Physical Exercise on Juveniles' Health Status and Subjective Well-Being in China"

18/10 *Silvia Balia, Rinaldo Brau, Daniela Moro,* "Hospital choice with high long-distance mobility"

18/09 *Luca Deidda, Ettore Panetti,* "Banks' Liquidity Management and Financial Fragility"

18/08 *Gerardo Marletto, Cécile Sillig,* "Lost in mainstreaming? Agrifood and urban mobility grassroots innovations with multiple pathways and outcomes"

18/07 *Jing Guan, J.D. Tena,* "Do Social Medical Insurance Schemes Improve Children's Health in China?"

18/06 *Carmenr Aina, Daniela Sonedda,* "Investment in education and household consumption"

18/05 *Maria Gabriella Campolo, Antonino Di Pino, Edoardo Otranto*, "Reducing Bias in a Matching Estimation of Endogenous Treatment Effect"

www.crenos.unica.it

ISBN 9788868512552